Naïve or Sophisticated? Information Disclosure and Investment Decisions in Peer to Peer Lending

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Abstract: Despite the explosive growth of peer-to-peer lending in China, information asymmetry remains a critical issue, and is likely to be rather amplified in this evolving credit market compared to a traditional credit market. This paper studies how investors screen the nonstandard, voluntary, and often unverifiable information disclosed by the borrowers to make their investment decisions. We use data from Renrendai, a leading lending platform in China. We find that an additional item of disclosure increases the funding probability by 23.6%. The impact is even more remarkable for the borrowers with lower credit rating. However, investment in the loan listings with more disclosures turn to be riskier. An additional item of disclosure is accompanied by 11.7% of incremental default probability. The puzzle that lenders remain attracted by such loan listings can be explained by the higher profitability offered by the borrowers. Further investigation shows that investors are actually able to infer the real risk of borrowers marked by the disclosure.

Key Words: Voluntary Information Disclosure; Manipulation; Information Asymmetry; P2P Lending;

1. Introduction

The online peer-to-peer (P2P) lending platforms has emerged as an alternative to traditional lending institutions around the world (Sorenson *et al.* 2016). These platforms bypass banks, by capitalizing on the advance of digital technology. The online P2P lending is a special type of credit market in which individual engage in lending practices. The lenders provide microloans to borrowers without collateral or the mediation of financial intermediaries (Lin *et al.* 2013). The P2P lending facilitates easy to access finance online for small borrowers (Paravisini *et al.* 2017) and higher rate of return for investors (Duarte *et al.* 2012) compared to the traditional credit. Information asymmetry seem to be a critical and a rather magnified issue in such evolving market, relative to the traditional credit market (Herzenstein *et al.* 2011). Hence, in the later financial intermediaries' role is to evaluate and monitor borrowers' creditworthiness and accordingly, make professional lending decisions. In P2P lending market, both lenders and borrowers are anonymous and don't have opportunities of meeting each other. The platform act as match maker refraining from conducting any function that implies financial intermediation. The lenders make the investment decision mainly based on the standard financial information as well as nonstandard information voluntarily disclosed by the borrowers (Iyer et al., 2016). There is a sizable literature that has extensively investigated the role of disclosure, particularly the mandated and audited financial reports, in mitigating information asymmetry in the financial markets (Brockman *et al.* 2008; Brockman *et al.* 2010; Zhao *et al.* 2013; Balakrishnan *et al.* 2014; Chung *et al.* 2015; Goldstein & Yang 2019). Nonetheless, little is known about the information disclosure by individuals in a peer-to-peer context. The information disclosure in such information opaque market is likely to influence the investment decisions by investors and indeed may shape the future of such new but rapidly growing fintech market.

This study fills the gap in the literature by capitalizing on opulence of the Chinese P2P lending market. We use a unique data from Renrendai, one of the leading P2P lending platforms in China, to study the voluntary disclosures by the borrowers and its impact on market efficiency. China has developed the biggest and fastest growing market for online P2P lending. In 2016, the transaction volume of P2P lending nationwide exceeded 2.8 trillion yuan (US$ 403 billion), with an increase of 138 percent from a year earlier.[2] Figure 1 plots the volume of transaction in Chinese P2P lending market from 2013 to 2017. The Chinese government has encouraged the development of online finance to promote alternative sources of funding for consumers and small businesses who have long struggled to access finance from stodgy state-owned banks (SOBs). In China SOBs are tilted toward lending to large companies or those borrowers with sufficient tangible assets to pledge as collateral. Despite the explosive growth of Fintech, social credit system remains underdeveloped in China and other emerging economies. In high income countries where the credit system is well established, many platforms, like Smava in Germany, only allow loan applications by borrowers with a certain minimum credit score (Dorfleitner *et al.* 2016). On such platforms, investors rely heavily on hard information like credit scores while the effect of soft information on the funding success and default rate is limited. At inception,

[2] http://www.chinadaily.com.cn/business/2017-01/05/content_27866083.htm

most of the Chinese platforms did not have credit scores for borrowers. As of 2014, the People's Bank of China maintained credit histories for around 350 million citizens, less than one-third of the adult population (in America 89% of adults have credit scores).[3] Under such conditions, the information asymmetry in P2P lending market is likely amplified. The voluntary disclosure by the borrowers is the main information source for investors to infer the credit quality and make investment decisions. Therefore, it is important to explore the various mechanisms through which the information asymmetry between borrowers and lenders could be moderated (Strausz 2017).

**********Insert Figure 1 here**********

Analyzing 604,885 loan listings posted on Renrendai, we find that voluntary disclosure plays a significant role in forming lenders' investment decision. A single item of voluntary information disclosure enhances the funding success rate by 23.6%. The impact is even more remarkable for the borrowers with lower credit rating. We compare the influence of both verified and unverified information on the probability of funding. Our findings show that borrowers with more verified information are more likely to get a loan. However, investment in the loan listings with more disclosures turn to be riskier. Borrowers who list additional item of disclosure are likely to increase their default probability by 11.7%. Our results imply the possibility of information manipulation by the borrowers in Chinese P2P market. In other words, the results reveal a dark side of P2P lending confirming borrowers' Moral Hazard behavior. Poor-quality borrowers exploit the high level of information asymmetry and the lack of hard information by disclosing more information to capture funding however with a premediated intention to default. These poor-quality borrowers may self-select to disclose false information, to mimic the good-quality to acquire loans. Such manipulation of disclosure exacerbates market inefficiency arising from information asymmetry. We find that factors such as education, work experience and income play a much larger role in affecting the investors' choice than other information. The well-educated borrowers may choose to disclose his or her degree while conceal other important information that may reflect a real financial risk.

There is an important question seems to impose itself in our study - Are investors sophisticated enough to infer the real credit quality of borrowers with the given amount and quality of information voluntarily provided by the borrowers. We find that lenders are able to infer the real risks not reflected by the disclosures. They are reluctant to invest in the loan listings with higher level of real default probability. It takes longer time and needs more bids for such loan listings to get funded. A possible explanation for the puzzle that lenders remain attracted by the loan listings with more disclosure is profitability. The higher default risk is, the higher profitability offered by the borrowers (higher interest rate). The empirical evidence suggests that loans listed with more voluntary information disclosure are more likely to defaulted, despite the higher interest rate offered by the borrowers as compensation for such risk. At the same time, those loans with more voluntary information disclosure have higher expected profit,

[3] https://www.economist.com/news/finance-and-economics/21710292-chinas-consumer-credit-rating-culture-evolving-fastand-unconventionally-just

but less loss when default. Therefore, it appears as an appealing choice for lenders to invest in loans with more voluntary information disclosure.

In evaluating the impact of disclosure on investment choice, there are a number of important endogeneity concerns that need to be addressed. First, as default depends on success, we can only observe the defaults among the borrowers who have successfully get their loan requests funded but cannot observe defaults by those who fail to raise the fund. Hence our estimation on the default might be susceptible to the sample selection bias. In addition, some unobservable or omitted variables may contaminate our estimation results. For example, social network and investor sentiment may change funding success rate (Grinblatt *et al.* 2011). We employ several empirical strategies to address these challenges, including the Heckman selection model and instrumental variable Probit model. In particular, we employ the widely recognized peer effect as the instrument for information disclosure (Chen 2015; Zhang *et al.* 2016; Kim *et al.* 2017; Adhikari & Agrawal 2018; Eom 2018; Hasan & Cheung 2018; Huang & Mazouz 2018; Jiang & Yuan 2018; Ward *et al.* 2018). The empirical results show that our conclusions are robust across different estimations after controlling for endogeneity.

Our study is an important addition to the limited yet growing literature on P2P lending (*inter alia* Duarte *et al.* 2014; Pope and Syndor 2011; Lin *et al.* 2013 and Lin and Viswanathan 2016). Our work is different from the study of Michels (2012) that investigates the effect of information disclosure on funding cost using the data from the Prosper platform in the US. His study focuses on the implications of the non-voluntary disclosure by borrowers that can lead to reduction of borrowing cost. In our study, we rather emphasis the role of voluntary disclosure and unverifiable information. We argue that both voluntary disclosure and unverifiable information might be used by borrowers as a signal of creditability hence providing incentives for lenders to invest. The Moral Hazard behavior by borrowers manifested in the deceptive signaling is likely to lead to a higher probability of default and hence the loss of investors' wealth. The long-term policy implication of such acts may result in loss of confidence and slow-down of the industry. Our results reveal how the borrowers strategically disclose in the market where the social credit system is underdeveloped, and its impact on investment decision. The implications of voluntary and unverifiable information is likely to be augmented in Chinese market considering the relatively high level of information opaqueness compared to developed market.

Disclosure plays an important role in improving the efficiency of financial markets. Previous literature indicates that disclosure is associated with stock performance, bid-ask spreads, cost of capital, analyst coverage and institutional ownership. Empirical evidence show that imposing minimum disclosure requirements attenuates the information asymmetry between informed and uninformed investors (Hirshleifer & Teoh 2003; Ball *et al.* 2012; Bertomeu & Magee 2015). Our research extends the existing literature on information asymmetry that is detrimental to the efficiency of financial markets. We provide evidence from the evolving P2P market that has little known about. Despite the current believe that disclosure is an important tool to reduce the adverse implications of information asymmetry, our result reveals that investors' moral hazard offsets the benefits of involuntary disclosure and leads to market inefficiency. In a market that can be described as being both evolving and information opaque, investors should investigate the quality of information and demand verification of what is disclosed by borrowers. Empirical evidence from psychology and behavior economics literature claims that uninformative material influence behavior and choices significantly (Bertrand & Morse 2011). Nonetheless, the role of voluntary and unverifiable information in screening credit quality of borrowers and its impact on investment decisions is still ambiguous (Bernardo *et al.* 2004). Our study provides interesting evidence in this vein by showing that voluntary and unverifiable information has a significant influence on lenders' inference of borrowers' creditworthiness even when standard financial information like credit scores are not available.

The remainder of this paper is organized as follows. Section 2 reviews related literature; Section 3 describes our dataset and measurement of key variables; Section 4 reports the main results; Section 5 addresses the endogeneity concerns; Section 6 summarizes the various robustness checks; and Section 7 concludes the paper.

2. Related Literature

Since the seminal contributions of Akerlof (1970), Spence (1973), and Stiglitz and Weiss (1981), the link between lemon theory and disclosure is widely tackled in the literature (Leftwich *et al.* 1981; Bhattacharya & Ritter 1983; Hughes 1986; Pownall & Waymire 1989; Teoh & Hwang 1991; Pae 2002; Ghose 2009; Lewis 2011; Tadelis & Zettelmeyer 2015). Disclosure is seen as a main solution to the information asymmetry that impedes the efficient allocation of resources in the capital market. Healy and Palepu (2001) shows that financial accounting and reporting is a mechanism to moderate information asymmetry by converting inside information into public information. Kothari (2001) suggests that reducing information asymmetry has desirable effects on the cost of capital and the volatility of security prices, which motivate regulators to strive for high-quality accounting standards. Examining the *ex ante* effects of public information quality on market prices, Barron and Qu (2014) conclude that high-quality public disclosure leads to increased price efficiency and decreased cost of capital in the pre-announcement period when information asymmetry is high. Studying the information-gathering role of a startup accelerator, Kim and Wagman (2014) demonstrate that when some signals are uninformative and the portfolio consists of mostly high-quality ventures, the accelerator may choose to disclose only positive signals (and conceal negative signals) about its portfolio. Cheng *et al.* (2013) find that firms that are eligible to reduce their disclosure, but voluntarily maintain their disclosure level, experience an increase in market illiquidity. Vashishtha (2014) show that firms reduce disclosure following covenant violations and part of this decline in disclosure reflects a delegation of monitoring to banks by shareholders who consequently demand less disclosure.

The existing literature suggests that although most information accessible to investors in traditional lending markets is nonstandard, unverifiable or "soft", they are valuable about borrower creditworthiness (Inderst & Mueller 2007; Agarwal & Hauswald 2010; Keys *et al.* 2010; Keys *et al.* 2012; Rajan *et al.* 2015; Bertomeu & Marinovic 2016). Early research on information asymmetry and disclosures has typically assumed that disclosures must be made truthfully and signals are costless and verifiable (Bagnoli & Watts 2007). However, the seminal paper of Crawford and Sobel (1982) has triggered more and more researchers to explore scenarios where the disclosures are not necessarily truthful. In the "cheap-talk" games, disclosures can even be false. Gigler (1994) shows that even when disclosures are unverifiable, the cost associated with disclosure lends it credibility. Analyzing self-reported anticorruption efforts, Healy and Serafeim (2016) conclude that on average, firms' disclosures signal real efforts to combat corruption.

In a word, while traditional theory argues that unverifiable disclosures should be irrelevant, more and more evidences indicate that unverifiable information affects investment decision. Without intermediation from the financial institutions, P2P lending platforms provide a decentralized and market-based mechanism that facilitates investors to screen creditworthiness of borrowers by aggregating information disclosed by borrowers. Besides the standard and hard financial information commonly used by banks, such as the borrower's income and credit report, lenders can view nonstandard, unverifiable and less quantifiable information, such as the maximum interest rate the borrower is willing to pay, a textual description of purpose of borrowing, and the borrowers' personal information like age, employment, marriage status, living place, etc. If investors are influenced by the voluntary and unverifiable disclosures made by borrowers in their loan listings, the funding probability shall increase with the amount of disclosures.

However, the impact of information disclosure on the funding success haven't reached consensus yet. According to Wittenberg-Moerman (2008) 's research on the secondary market transactions of syndicated loans, investors are more sensitive to the economic returns of those discount loans than those of flat loans. In other words, when investors evaluate the claims of these borrowers, the good news will be more important. Wittenberg-Moerman (2008) also confirmed in the empirical analysis that the borrower's timely financial report did not have a significant impact on the bid-ask spread in loan transactions. This implies that more financial information does not necessarily enhance investors' trust in borrowers and funding success rate because some particular information may trigger discrimination against the borrowers. For example, using data from Prosper.com, the leading P2P lending platform in US, Pope and Sydnor (2011) find evidence of significant racial disparities. Loan listings by blacks are less likely to receive funding than those of whites with similar credit profiles while the interest rate paid by blacks is higher than that by comparable whites. Employing similar data, Duarte *et al.* (2012) show that borrowers appearing more trustworthy are more likely to have their borrowing requests funded. The empirical evidences provided by Lin and Viswanathan (2016) suggest that home bias is a robust phenomenon even in the context of a large online crowd funding marketplace. This series of studies have shown that the borrowers' voluntary disclosure of information does not necessarily lead to higher probability of funding success. In contrast, some information like gender, race or low income may even trigger discrimination toward borrowers and hence lower the funding probability.

Michels (2012) claim that voluntary information disclosure can reduce interest rate and default rate based on the theory of cheap talk and behavioral economics that people tend to believe whatever information they can get, and it is difficult to ignore the irrelevant information in decision-making. A large number of studies have shown that corporate voluntary information disclosure can moderate the cost of capital. Balakrishnan *et al.* (2014) find that voluntary disclosure is beneficial for a firm by improving its liquidity, increasing its market value and reducing its capital cost. Dhaliwal *et al.* (2014) document that disclosure a company's corporate social responsibility can significantly reduce its cost of equity capital. The research of Jones (2007) also confirms that the voluntary disclosure of R&D input could lower the proprietary cost. Francis et al. (2008) assert that companies with good earnings quality are likely to disclose more sufficient information, suggesting a complementary relationship between earnings quality and voluntary information disclosure. At the same time, voluntary information disclosure can reduce the cost of capital, increase stock liquidity and reduce operation risks. Francis *et al.* (2005) propose that enterprises that rely on external financing are more likely to make a higher level of information disclosure, which leads to a lower external financing cost, and this conclusion is independent of factors at the national level and can be widely held in the worldwide. In the lending market, we believe that high-quality borrowers have good reasons to voluntarily disclose more information to lower the borrowing rate and improve the borrowing success rate.

Some research has found that companies are more likely to engage in manipulation when voluntary disclosure is closely related to the response of capital market (Evans 2016; Devos *et al.* 2015; Kumar *et al.* 2012). Wen (2013) find that the management might disclose information beneficial to the company because voluntary disclosure affects its stock price. Roychowdhury and Sletten (2012) believe that the management has strong incentives to avoid disclosing bad news. In addition, the risk faced by the company also affects the voluntary disclosure of information. Zechman (2010) claims that facing cash constraints, the management is more reluctant to disclose the transaction information of financial assets. Nelson and Pritchard (2016) show that companies facing high litigation risk would improve the quality of voluntary disclosure. Beyer and Guttman (2012) prove that when management could obtain favorable conditions, they would manipulate voluntary information disclosure. In the credit market, borrowers have the best understanding of their ability and willingness to repay the loan. They may manipulate the content of information disclosure in order to win the trust of lenders and acquire loans. Such manipulation, in turn, implies a potential positive relationship between default probability and the amount of information disclosed voluntarily.

Voluntary information disclosure is accompanied by impression management, the behavior through which people influence others' perception of themselves (McDonnell & King 2013). Individuals form impressions of others in social interactions and extend them accordingly (Bansal & Clelland 2004; Davidson *et al.* 2004; Barsness *et al.* 2005; Hayward & Fitza 2017). Although the proverb says "don't judge a book by its cover", people still rely on the appearance of things to make decisions in most cases (Langlois *et al.* 2000). According to the study of Foulk and Long (2016), new employees will adopt the behavior of catering to the supervisor to conduct impression management, because for new employees, their future development is largely determined by their supervisor. The existing literature in P2P lending suggests that borrowers design and form their own image by using positive words in loan description to show the strong willingness of repayment (Herzenstein *et al.* 2011). But such impressive-management incentive can lead borrowers to disguise information that is relevant to the real credit risk (Leary & Kowalski 1990; Morrison & Bies 1991).

3. Data Source, Key Variable Measurement and Summary Statistics

3.1 Data Source

The data used in this study is obtained from Renrendai, one of the largest peer-to-peer lending platforms in China. Founded in 2010, it now has over 1 million members located in more than 2,000 cities or counties across the country. Moreover, the reputation of Renrendai has been well recognized in China. In 2014 and 2015, it was awarded as AAA (highest level) online lending platform by Internet Society of China and China Academy of Social Science. It ranked No. 53 in a list of China's top 100 internet companies released by the Internet Society of China and the Ministry of Industry and Information in 2015.

The transaction taking place at Renrendai is a typical P2P lending. On Renrendai, borrowers can post loan requests or listings with the required information of loan title, borrowing amount, interest rate, description of loan usage, and monthly installment. Renrendai only provides basic verification on borrowers' national identification cards, credit reports, and addresses. It assigns a credit score to each borrower according to his or her borrowing/lending history and the number of verified information. Akin to Prosper.com, Renrendai's profit mainly comes from borrower's closing fee and lender's servicing fee. Since the verification and credit rating provided by Renrendai is limited, it is hence of critical importance for the lenders to identify the trustworthiness of the borrowers from the observable information disclosed at the platform. In particular, when creating the loan listings, borrowers are encouraged to disclose additional information regarding the purpose of the loan and other personal information in a freeform text called the loan description. Figure 2 shows a typical loan request on Renrendai. Once a loan listing is posted online, lenders may place bids by stating the amount they want to fund. With a minimum bid amount of RMB 50, a listing typically requires dozens of bids to become fully funded. A listing that achieves 100 percent funding status is a "successful" listing; otherwise, the borrower receives zero funding.

**********Insert Figure 2 here **********

The transaction module of Renrendai is comparable to that of Prosper, the largest lending platform in US. The existing research (Duarte *et al.* 2012; Michels 2012; Zhang & Liu 2012; Lin *et al.* 2013; Iyer *et al.* 2016; Lin & Viswanathan 2016; Hildebrand *et al.* 2017) mainly uses data obtained from Prosper. On Prosper, borrowers post personal loan requests while investors (individual or institutional) can fund anywhere from $2,000 to $35,000 per loan request. In addition to credit scores, ratings, and histories, investors can use borrowers' personal loan descriptions, endorsements from friends, and community affiliations to make investment decision. Prosper handles the servicing of the loan and collects and distributes borrower payments and interest back to the loan investors. Prosper verifies borrowers' identities and select personal data before funding loans and manages all stages of loan servicing.

This study uses all loan listings created on Renrendai between January 1, 2011 and December 31, 2015. We eliminate the data earlier and later than this period to avoid the initial launch period and truncation on loan repayments respectively. The original sample include 795,110 listings. We also eliminate 190,225 listings guaranteed by the platform because they are not typical P2P lending. In addition, we winsorize the loan listings whose AMOUNT and AGE are at the top or bottom one percentile of their respective distributions to eliminate outliers. As a result, our sample includes 604,885 loan listings, of which 27,112 were successfully funded while the rest were not funded. We track the repayment performances of all successful loan listings. By the end of Sep 2017, there are 4,094 defaulted listings and 414 samples in progress of repayment.

3.2 Key Variables

3.2.1 Measurement of Information Disclosure

To gauge the effects of voluntary information disclosure on loan outcome and loan performance, we construct an information disclosure measurement. There are two kinds of information disclosure at Renrendai, compulsory disclosure and voluntarily disclosure. The compulsory information includes: (1) the borrowing amount, interest rate and term; (2) a borrower's age and assets like ownership of housing or car; (3) loan description, corresponding title and borrower's nickname.

There are nine items of voluntary information disclosures at Renrendai, including education, employment, income, marriage, living place, purpose of borrowing, etc. We award a point for each of them to construct the voluntary information disclosure variable. The detailed description of all these eight items are as follows.

Education: a borrower's education attainment. It is classified into four levels of high school or below, junior college, bachelor, and postgraduate and above.

Working experience: the length of time that a borrower has worked. It is classified into four categories of 1 year or less, 1-3 years, 3 to 5 years, and more than 5 years.

Income: a borrower's monthly income. It is classified into seven ranks of less than RMB 1000, 1001-2000, 2001-5000, 5001-10000, 10001-20000, 20001-50000, and more than 50000.

Marriage: the marital status of borrowers, including divorced, widowed, single or married.

Living place: the prefecture or district (of a municipality) that a borrower is living in.

Firm size: the size of the firm that a borrower is working for. It is classified into four categories of less than 10 employees, 10-100 employees, 100-500 employees and more than 500 employees.

Loan purpose: the usage of fund described by the borrowers, including short-term turnover, personal consumption, car loans, mortgage, wedding planning, education or training, investment, medical expenditure, home renovation, etc.

Industry: the industry that a borrower is working for, including IT, restaurant/hotel, the real estate, public utilities, public welfare organizations, computer systems, construction, transportation, education/training, finance, law, retail/wholesale, media/advertising, energy, agriculture, other, sports/arts, medical/sanitation/health care, entertainment, government agencies and manufacturing.

Position: the position that a borrower has in his working place, like clerk, manager, etc.

We denote the above-mentioned nine indicators of borrowers' voluntary information disclosure as Edu_Disclosure, Worktime_Disclosure, Income_Disclosure, Marry_Disclosure, City_Disclosure, Firmsize_Disclosure, Purpose_Disclosure, Ind_Disclosure and Position_Disclosure respectively. We then construct three indicators to measure the intensity of information disclosure, including DSCORE_ALL, DSCORE and DSCORE_NOR. We give a point to each component of information disclosed in a loan list. DSCORE_ALL is the sum of the points that a loan listing is awarded for all the information voluntarily disclosed. DSCORE is a dummy that is equal to one if a borrower discloses all the nine items of voluntary information, and zero otherwise. In our sample, almost all borrowers disclose the purpose of borrowing and marriage status. To avoid estimation bias, we construct an indicator of DSCORE_NOR to calculate the amount of the voluntary information disclosed except purpose of borrowing and marriage status. For example, in Figure 2 borrower's DSCORE_ALL equal 0, DSCORE equal 1 (only disclosed loan purpose), DSCORE_NOR equal 0.

In addition to the above variabls, we include two categories of control variables in the regression. The first is the information related with loan listings, including the term, interest rate, and borrowing amount, etc. The second is related with the credit risk of borrowers, including the credit score if any, mortgage,car loans, etc. Table 1 summarizes the definition of all variables used in this study.

**********Insert Table 1 here **********

3.2.2 Measurement of Loan Performance

In addition to the interest rate, we calculate the expected profit and expected loss of all loan listings to comprehensively measure the loan performance.

<u>*Expected profit*</u>

Assume that each loan is for $1, and if the borrower repays the loan, the lender receives $(1 + \mathrm{r})$, where r is the interest rate. This means that the lender earns a net profit of r if the borrower repays the loan, and loses the entire dollar if the borrower fails to repay the loan. If the default probability (DP) is δ, a lender's expected profit (EP) on a loan listing is $E[\pi] = (1-\delta)r - \delta$. To get the DP, the likelihood that a borrower defaults, we first estimate the following equation by the Probit model:

$$\Pr(DEFAULT_i) = \alpha_0 + \alpha_1 X_i + u_i \tag{1}$$

where the dependent variable indicates whether a loan listing *i* defaults after it is successfully funded. It equals 1 if the borrower defaults, and 0 otherwise. X_i is a vector of control variables including loan characteristics, borrower characteristics, and year effect. u_i refers to the error term. The coefficients estimated from equation (1) is then used to predict the default probability of each loan listing. With the default probability and interest rate, we are able to measure the expected profit for each loan listing.

Expected loss

Following the literature on credit risk management (Bessis, 2015), we define the expected loss (EL) of a loan listing as the product of loss given default (LGD) and DP, i.e.

$$EL = LGD \times DP.$$

We define LGD as the fraction of principal amount remaining if the borrower defaults at time t. According to the common practice applied at Renrendai, we assume that all loan listings are fully amortized. The borrower pays off the debt with a fixed monthly repayment schedule in equal installments so that the loan will be fully paid off at maturity. Hence, according to Hayre and Mohebbi (1992), LGD can be computed as follow:

$$LGD = 1 - \frac{(1 + r^m)^t - 1}{(1 + r^m)^n - 1}$$

where r^m is the monthly rate (i.e. the note rate divided by 12) and the loan term n is quoted in months. For the loan listings fully repaid at maturity, $t = n$, and hence $LGD = 0$. After computing LGD, we can get the repayment ratio (RR) for the problematic loans as $RR = 1 - LGD$.

3.3 Summary Statistics

Panel A of Table 2 shows the summary statistics for the components of information disclosure. Among the nine items of voluntary information, more than 96% of borrowers disclose their borrowing purpose and marital status, around 70% disclose their living city, the size of the firm and industry they are working for. Overall, most borrowers are willing to disclose as much personal information as possible so as to get their loan requests funded.

Panel B of Table 2 tests for the mean differences between funded and unfunded lists, as well as whether loan default. In terms of information disclosure, the mean of DSCORE for funded loan lists is 8.75, or 1.74 point significantly higher than that of unfunded loan lists. In addition, we also find that the mean of DSCORE for default loan is 8.83, or 0.1 point significantly higher than that of an loan for payment on time. Comparing with the loan lists that don't disclose all information, the lists with full information disclosure on average are 5% more likely to get loan request funded and are 6% more likely to default. Loan interest rate are also 0.93% higher.

**********Insert Table 2 here **********

Table 3 reports the correlation matrix of key variables. It is clearly noted that borrowing rate, amounts, term and the lengths of nickname are significantly and negatively correlated with funding success, whereas borrowers' credit rating, age, ownership of property and car, the lengths of borrowing title and borrowing description are significantly and positively associated with funding success. More importantly, all eight items of voluntarily disclosed information are positively correlated with funding success, interest rate and loan default.

**********Insert Table 3 here**********

Table 4 presents descriptive statistics of all variables used in this study. The average funding success rate is about 4.48%, among which 15.1% default, implying that the competition for funding is very tough in P2P lending market, but there are also high credit risk. On average, it takes about 122 minutes for each loan to raise money successfully. The average loan has about 25 investors. The average borrower has only 2.5 items of certified information. Borrowers had an average profit return of 19.82, an average loan recover rate of 0.421, and an average default loss of -709. Borrowers on average voluntarily disclose about 7.09 of 9 information items. The borrowers who voluntarily disclose all information account for 63.8% of all borrowers, implying that most borrowers are willing to disclose as much information as possible so as to transmit signals of trustworthiness to investors. The average borrowing rate is approximately 13.36% and the average borrowing amount is RMB 59,000 (around USD 10,000), indicating the role of P2P lending market in facilitating microfinance. The credit grades of borrowers are universally low with an average credit rating of 1.083. Most borrowers are youth in P2P lending market with an average age of around 32 years old. Additionally, 30.7% borrowers own houses and 17.8% borrowers have cars. The average length of loan title contains 13.72 Chinese characters and punctuations while the average length of loan description is 92.49 Chinese characteristics. The average length of borrower's nickname contains 9.7 Chinese characters and punctuations.

**********Insert Table 4 here**********

4. Main Results

We first examine the extent to which information disclosure and its intensity affects investment decision. We also compare the information disclosure by borrowers of different credit category and its impact on funding probability. Next, we explore whether information revealed by borrowers reflect their creditworthiness. Given the unexpected relationship between the disclosure and default, we further investigate whether investors are aware of the risks not reflected by disclosure. Finally, we focus on solving the puzzle that lenders remain attracted by loan listings with more disclosure but higher default probability by looking at the profitability of such listings.

4.1 Disclosure and Funding Success

The summary statistics show the significantly positive correlation between borrowers' voluntary disclosure and funding success rate. This section reports the regression results estimated by the logit model. We first estimate the following model:

$$SUCCESS_i = \beta_0 + \beta_1 Vol\_Disclosure_i + \beta_2 Control_i + \varepsilon_i, \tag{2}$$

where the dependent variable *SUCCESS* denotes whether a borrower successfully gets loan request funded. It equals one if a borrower's loan request is funded, and zero otherwise. *Vol_Disclosure* is a dummy variable indicating whether a borrower voluntarily discloses any of his or her personal information, including education, income, working time, living place, size or industry of the firm he or she is working for, position, or borrowing purposes. Because almost all borrowers disclose their marital status, we do not include them in the estimation. We control other variables that might affect funding probability, including the characteristics of loan listing, borrowers' age, financial assets, length of loan description, etc. ε_i is random disturbance term.

**********Insert Table 5 here**********

Table 5 reports the estimation results. Column (1) summarizes the regression result on the variables that have been widely used to explain the probability of funding success. Consistent with existing researches, loan requests with lower interest rates or amount, longer term, longer title and loan descriptions are more likely to be funded (Liu *et al.* 2015; Dorfleitner *et al.* 2016; Iyer *et al.* 2016). Moreover, the funding probability is higher for borrowers with higher credit rating, of elder age, or owning houses or cars. Column (2) indicates that after adding the variable of Edu_Disclosure in the regression, Pseudo R^2 increases from 0.301 to 0.313. This means that borrowers' voluntary disclosure of education achievement can explain additional 1.2% of funding probability. In addition, the coefficient of Edu_Disclosure is positive and significant at 1% level, implying that disclosure of education can significantly improve funding success.

In Columns (3)-(9), we add the information components of Worktime_Disclosure, Income_Disclosure, City_Disclosure, Firmsize_Disclosure, Purpose_Disclosure, Ind_Disclosure and Position_Disclosure respectively. Pseudo R^2 is improved by degrees varying from 0% to 2.6%, and the coefficients are all significantly positive. These results indicate that borrowers' voluntary information disclosure is effective and has strong explanatory power on borrowing success rate. Among all components of information disclosure, living place, working time and income play the most important roles in raising the funding probability.

We further explore the relationship between intensity of disclosure and funding probability with the following the equation:

$$SUCCESS_i = \beta_0 + \beta_1 Disclosure\_Int_i + \beta_2 Control_i + \varepsilon_i. \quad (3)$$

We use three indicators to measure the intensity of information disclosure ($Disclosure\_Int$), including *DSCORE_ALL*, *DSCORE* and *DSCORE_NOR*. *DSCORE_ALL* is a dummy that is equal to one if a borrower discloses all nine components of voluntary information and zero otherwise; *DSCORE* is the sum of all points that a loan listing is awarded for all the information voluntarily disclosed by its borrower; and *DSCORE_NOR* is the sum of all points that a loan listing is awarded for all the voluntary information disclosed excluding purpose of borrowing and marriage status.

**********Insert Table 6 here**********

Table 6 summarizes the estimation results. In Columns (1), (3) and (5) of Table 6, we separately estimate the impacts of *DSCORE_ALL*, *DSCORE*, and *DSCORE_NOR* on funding success and show the corresponding marginal effects in Columns (2), (4) and (6). Comparing with Column (1) in Table 5, we find that Pseudo R^2s of Columns (1), (3) and (5) in Table 6 are improved by varying degrees, implying that the quantity of information disclosure generates incremental explanatory power on borrowing success rate. Column (2) shows that the marginal effect of *DSCORE_ALL* is 0.0343 and significant at 1% level. This means that after controlling for other factors, the funding success rate of a loan request with complete information disclosure is 76.5% higher than its counterpart with incomplete information disclosure (0.0343/0.0448). The marginal effect of *DSCORE* in Column (4) is 0.0106 and significant at 1% level. This implies that one additional component of voluntary disclosed information will enhance borrowing success rate on average by 23.6% (0.0106/0.0448). These results indicate that borrowers' voluntary information disclosure plays a very important role in enhancing the funding probability.

The impact of voluntary information disclosure on funding success might differentiate across borrowers of different risks. Borrowers with good credit are easy to signal their trustworthiness by virtue of verifiable and hard information like credit report issued by the crediting authorities. They can easily obtain bids and fund without disclosing much information. However, potential borrowers with poor credit have to rely more heavily on the information disclosure to differentiate themselves from other competing borrowers with poor credit (Michels 2012). This will induce them to disclose more information than borrowers having high credit rating. To test the differentiated impacts of disclosure on funding success across borrowers of different level of risks, we estimate the following model:

$$SUCCESS_i = \beta_0 + \beta_1 Disclosure_i + \beta_2 POOR_i + \beta_3 Disclosure_i \times POOR_i + \beta_4 Control_i + \varepsilon_i \qquad (4)$$

where *POOR* is a dummy variable that equals one if a borrower's credit rating is HR, and zero otherwise. *Disclosure*×*POOR* is the interaction term between the intensity of borrowers' voluntary disclosure and credit rating.

**********Insert Table 7 here**********

Table 7 presents the corresponding regression results. In Columns (1), (3) and (5), we estimate the effect of the interaction terms of *DSCORE_ALL*×*POOR*, *DSCORE*×*POOR* and *DSCORE_NOR*×*POOR* on funding probability respectively. Columns (2), (4) and (6) report the corresponding marginal effects. The estimation results reveal that the positive relationship between funding success rate and disclosures is stronger for borrowers with relatively low credit quality. Column (2) shows that the marginal effect of *DSCORE_ALL*×*POOR* is 0.0422 and significant at 1% level. This means that after controlling for other factors, the funding success rate for borrowers with complete information disclosure and low credit rating is approximately 94% higher than those with bad credit rating (0. 0422 /0.0448) but incomplete information disclosure. The marginal effect of *DSCORE*×*POOR* in Column (4) is 0.0123 and significant at 1% level, indicating that all else equal, one additional component of information voluntarily disclosed by a borrower of high risk will enhance his/her funding success rate by 27.4%

(0.0123/0.0448). The marginal effect of $DSCORE\_NOR \times POOR$ in Column (6) is 0.0124 and significant at 1% level, suggesting that all else equal, one additional item of voluntary information excluding borrowing purpose and marital status will increase funding success rate by 27.6% (0.0124/0.0448). These results imply that disclosure is highly valuable for borrowers of high risk because it helps to alleviate the negative effect of low credit rating on funding success.

4.2 Disclosure and Default

The above empirical results imply that borrowers shall be aware of the importance of disclosure. Given the low cost of disclosure, a borrower may manipulate the information he or she reveal to the investors to conceal bad credit information and acquire a loan. Hence, a natural question is whether voluntary disclosure truly reduces the informational disadvantages that lenders face in the P2P lending platform. We hence explore the relationship between disclosure and the probability of default with the following equation

$$DEFAULT_i = \beta_0 + \beta_1 Disclosure\_Int_i + \beta_2 Control_i + \varepsilon_i \tag{5}$$

where the dependent variable *DEFAULT* indicates whether a loan listing i defaults after it is successfully funded. It equals 1 if the borrower defaults, and 0 otherwise. $Disclosure\_Int$ is the indicator measuring the intensity of information disclosure, including *DSCORE_ALL*, *DSCORE* and *DSCORE_NOR*. We control the variables that might affect funding probability, including the characteristics of loan listing, borrowers' age, financial assets, length of loan description, etc. ε_i is random disturbance term.

**********Insert Table 8 here**********

Table 8 reports the regression results. In Columns (2), (4) and (6), we separately estimate the impacts of *DSCORE_ALL*, *DSCORE*, and *DSCORE_NOR* on the probability of default. Columns (3), (5) and (7) show the corresponding marginal effects. Comparing with Column (1), we find that Pseudo R^2s of Columns (2), (4) and (6) are improved by varying degrees, implying that the quantity of information disclosure generates incremental explanatory power on default. Column (3) shows that the marginal effect of *DSCORE_ALL* is 0.0447 and significant at 1% level, meaning that after controlling for other factors, the probability of default of a loan with complete information disclosure is 29.6% higher than its counterpart with incomplete information disclosure (0.0447/0.151). The marginal effect of *DSCORE* in Column (5) is 0.0177 and significant at 1% level, suggesting that one additional component of voluntary disclosed information will enhance the probability of default on average by 11.7% (0.0177/0.151). The marginal effect of *DSCORE_NOR* in Column (7) is 0.0179 and significant at 1% level. This implies that all else equal, one additional item of voluntary information excluding borrowing purpose and marital status will increase the probability of default on average by 11.8% (0. 0179/0.151).

Our findings are different from Michels (2012) who found that disclosure has a strong and negative association with future defaults. Our results reflect the possibility of information manipulation by the borrowers in Chinese P2P market with a high level of information asymmetry between lenders and borrowers due to lack of hard information for most borrows. Under such a situation, lenders are more likely to depend on soft information disclosed by borrowers. However, the evidence we show here suggest that the extent to which such information is related to borrowers' fundamental default risk is questionable. On one hand, the borrowers may choose to disclose the information in their favor. For example, according to our estimation, disclosures of education, working experience and income plays a much larger role in affecting the investors' choice than other information. The well-educated borrowers may choose to disclose his degree while conceal other important information on their real risks. On the other hand, the information disclosed by the borrower is hard to be verified. The poor-quality borrowers may self-select to disclose false information, to mimic the good-quality to acquire loans. Such manipulation of disclosure will exaggerate market inefficiency arising from information asymmetry.

4.3 Verified Information and Loan Outcome

In the financial market, the verified financial information is the key signal to transmit information to the market, generally speaking, the verified information will be more credible(Greenwood *et al.* 2010; Brown *et al.* 2012; Ben-Porath *et al.* 2014). As mentioned before, Renrendai provides basic verification on borrowers' national identification cards, and credit reports. Borrower can also provide some other information to be verified by the platform. Take marriage certification as an example, the specific way is that the borrower takes photos of the marriage certificate and uploads it to the platform. However, the uploaded certificate could be faked and Renrendai is not able to check every single details of seemingly verifiable information. Even so, information certification can reflect the extent to which borrowers are trying to obtain loans. So how does information certification affect the loan outcome? We estimate the following model:

$$Loan\ Outcome_i = \beta_0 + \beta_1 Disclosure_i + \beta_2 Ver\_Numb_i + \beta_3 Disclosure_i \times Ver_{Numb\,i} + \beta_4 Control_i + \varepsilon_i \quad (6)$$

where *Loan Outcome*$_i$ is the loan outcome variable of loan listing i. It contains three variables, *SUCCESS*, *INTEREST and DEFAULT* respectively. *Disclosure* are indicators measuring the intensity of information disclosure, including *DSCORE_ALL*, and *DSCORE. Ver_Numb* is the number of information verifications. It contains the amount of information verified by the platform, including whether 11 items, such as a borrower's national identification cards, and credit reports, job or income, etc have been verified by the platform. *Disclosure×Ver_Numb* is the interaction term between the intensity of borrowers' voluntary disclosure and the number of information verifications. We control other variables that might affect funding probability, interest rate, and the probability of default, including the characteristics of loan listing, borrowers' age, financial assets, length of loan description, etc. ε_i is random disturbance term.

**********Insert Table 9 here**********

Table 9 presents the corresponding regression results. In Column (1) and Column (2), the estimated results of *Ver_Numb* and its interaction with *Disclosure* relative to funding probability are presented. In Column (3) and Column (4), the estimated results of *Ver_Numb* and its interaction with *Disclosure* relative to interest are presented. In Column (5) and Column (6), the estimated results of *Ver_Numb* and its interaction with *Disclosure* relative to the probability of default are presented. According to the empirical results, the effect of *Ver_Numb* on funding probability is positive and significant at 1% confidence level , but *Ver_Numb* does not have a significant impact on interest rate and the probability of default. This result means that borrowers with more verified information are more likely to get a loan. The interaction of *Ver_Numb* and *Disclouse* will only have a significant impact on funding probability. It can be seen from the results of columns (1) and (2) that the impact of *Ver_Numb_DSCORE_ALL* and *Ver_Numb_DSCORE* on funding probability is negative and significant at 1% confidence level. This result implies that there is a substitution relationship between the number of verified information and voluntary information disclosure.

This is particularly important for China that doesn't have a widely accepted system to gauge creditworthiness among a fast-expanding middle class with growing paychecks, a hunger for consumer products and little or no credit history. Under such situation, the cost of default would be lower than that in the industrial countries like US where most adults rely on their credit score to reveal their creditworthiness and the default would significantly lower their credit score. Therefore, lenders on Chinese P2P lending market tend to trust borrowers with more verified information. However, the uploaded certificate could be faked and Renredai is not able to check every single details of seemingly verifiable information. China currently lacks an effective social credit evaluation system, so unilateral information verification on the P2P lending platform cannot fully verify the authenticity of information under the condition of online (cheap talk).

4.4 Disclosure and Risk Screening

The findings presented in above two subsections reveal that borrowers might manipulate disclosures to acquire loans. An important question is hence whether investors are sophisticated enough to infer the real credit quality that might be marked by information voluntarily provided by the borrowers. To answer this question, we assume that the same amount of disclosure corresponds to the same level of default risk if the market is fully efficient (Fama 1970, 1991). In other words, investors can infer the default probability of the borrower by the amount of information voluntarily disclosed by the borrower. However, given that borrowers may disclose their information strategically under the premise of cheap talk, the two loans with the same voluntary disclosure may contain different level of risks. Investors hence have to infer the credit quality using the information other than voluntary disclosures. To measure the risk of default reflected by disclosures, we first estimate the equation of

$$DEFAULT_i = \beta_0 + \beta_1 Disclosure_i + \varepsilon_i. \tag{7}$$

The coefficients estimated by equation (7) are used to predict the default risk captured by disclosures, i.e., $\Pr(\mathrm{DEFAULT}_i|Disclosure_i)$. Similarly, using the coefficients estimated by equation (5), we can measure the default risk captured by all information observable to the investors as $\Pr(\text{DEFAULT}_i|Disclosure_i, Control_i)$. Therefore, the default risk that is not reflected by voluntary information disclosure can be computed as

$$defalut\_risk_i \equiv \Pr(\text{DEFAULT}_i|Disclosure_i, Control_i) - \Pr(\text{DEFAULT}_i|Disclosure_i). \quad (8)$$

If lenders are sophisticated enough, they can screen out the default risk not revealed by the voluntary information disclosure and make rational investment choice. Given that smart investors shall be reluctant to invest in the loan listings with higher level of default risk, the loan listings with higher level of default risk needs more bids and longer time to get loan funded. This assumption can be tested by the following two equations:

$$FundTime_i = \beta_0 + \beta_1 default\_risk_i + \beta_2 Control_i + \varepsilon_i \quad (9)$$

$$BIDS_i = \beta_0 + \beta_1 default\_risk_i + \beta_2 Control_i + \varepsilon_i \quad (10)$$

The empirical results are shown in table 10. Column (1) and Column (2) report the coefficients estimated for equation (7) and (9). The Pseudo R^2 of the model (1) is just 0.2%, meaning that in the P2P lending market, voluntary information disclosure only reflects the limited amount of default risk. In Column (2), information other than disclosure is added, including the characteristics of loan listing, borrowers' age, financial assets, length of loan description, etc. Pseudo R^2 of the model (2) increases to 28.2%, suggesting that information other than disclosures are important to infer the credit quality.

**********Insert Table 10 here**********

We further estimated the impact of $default\_risk_i$ on *FundTime* and *BIDS*. The empirical results reported in Columns (3) and (4) show that the influence of $default\_risk_i$ on the number of bids and the funding time are both positive and significant at the confidence level of 1%. For a successful loan listing, a 10% increase in $default\_risk_i$ will raise the funding time by 72 minutes, and the number of bids by 18. Our results confirm that lenders are aware of the risks not reflected by voluntary disclosures.

4.5 Disclosure and Profitability

A possible explanation for the puzzle that lenders remain attracted by the loan listings with more disclosures but high default risk is the higher profitability offered by the borrowers. To test this hypothesis, we first explore the relationship between intensity of disclosure and interest rate with the following the equation:

$$Interest\ Rate_i = \beta_0 + \beta_1 Disclosure_i + \beta_2 Control_i + \varepsilon_i \quad (11)$$

where *Interest Rate* denotes the interest rate offered by a borrower. *Disclosure* are indicators measuring the intensity of information disclosure, including *DSCORE_ALL*, *DSCORE* and *DSCORE_NOR*. We control other variables including the characteristics of loan listing, borrowers' age, financial assets, length of loan description, etc. ε_i is random disturbance term.

**********Insert Table 11 here**********

Table 11 lists the regression results. In Columns (2), (3) and (4), we separately estimate the impacts of *DSCORE_ALL*, *DSCORE*, and *DSCORE_NOR* on interest rate. Comparing with Column (1), we find that Adjusted R^2 of Columns (2), (3) and (4) are higher by varying degrees, implying that the quantity of information disclosure generates incremental explanatory power on loan interest rate. Column (2) shows that the coefficient of *DSCORE_ALL* is 0.133 and significant at the 1% confidence level. This means that after controlling for other factors, the loan interest rate of a loan request with complete information disclosure is 1% higher than its counterpart with incomplete information disclosure (0.133/13.36). The coefficient of *DSCORE* in Column (3) is 0.02 and significant at 1% level. This implies that one additional component of voluntary disclosed information will enhance loan interest rate on average by 0.14% (0.02/13.36). The estimates in Column (4) are similar to those in Column (3).

Our result is contrary to Michels (2012) who finds that more disclosure results lowers funding cost. We believe that this also reflects the borrowers' disclosure manipulation. In P2P lending market, the interest rate of borrowing is the key indicator for lenders, because it is related to the return on investment of lenders. Therefore, borrowers who adopt the behavior of information disclosure manipulation are more likely to set a higher interest rate to meet the needs of lenders to attract them to invest, so as to achieve the purpose of successfully obtaining loans, which, on the contrary, results in higher interest rates set by borrowers with more voluntary information disclosure.

We further examine the effect of voluntary disclosure on loan performance with the following model:

$$Loan\ Performance_i = \beta_0 + \beta_1 Disclosure_i + \beta_2 Control_i + \varepsilon_i \qquad (12)$$

where *Loan Performance*$_i$ is measured by three indicators of expected profit (*EP*), loan repayment ratio (*LRR*) and default loss (DL) respectively. *Disclosure* are indicators measuring the intensity of information disclosure, including *DSCORE_ALL*, *DSCORE* and *DSCORE_NOR*. We control other variables that might affect funding probability, interest rate, and the probability of default, including the characteristics of loan listing, borrowers' age, financial assets, length of loan description, etc. ε_i is random disturbance term.

**********Insert Table 12 here**********

Table 12 presents the corresponding regression results. In Columns (1)-(9), we separately estimate the impacts of *DSCORE_ALL*, *DSCORE*, and *DSCORE_NOR* on expected profit, loan repayment ratio, and default loss. We find that *Disclosure* can have a significant impact on expected profit and default loss, but not on loan repayment ratio. The coefficient of *DSCORE* reported in column (4) is 0.003 and significant at the 1% confidence level, meaning that the more voluntary information disclosures there are, the higher the expected profit will be. The coefficient of *DSCORE* is negative and significant at the 1% confidence level. All these results suggest that although the loan listings with more voluntary information disclosure are more likely to be defaulted, the higher interest rate offered by the borrowers can compensate for the risk. At the same time, those loan listing with more voluntary information disclosure have less loss when default. Therefore, it is still the best choice for lenders to invest in loan listings with more voluntary information disclosure.

5. Endogeneity Concerns

In evaluating the impact of voluntary disclosure information on loan outcomes, there are a number of important methodological challenges that need to be addressed. First, as default depends on success, we can only observe the defaults among the borrowers who have successfully get their loan requests funded but cannot observe defaults by those who fail to raise the fund. Hence our estimation on the default might be susceptible to the sample selection bias. Heckman Selection Model is adopted to moderate this bias (Heckman 1979). Second, some unobservable or omitted variables may contaminate our estimation results. For example, social network and investor sentiment may change funding success rate (Grinblatt *et al.* 2011). We employ the IV Probit model and 2SLS model to address this concern.

5.1 Heckman Selection Model

One methodological challenge of this study is that default is dependent on success. We can only observe the defaults by the borrowers who have successfully get their loan requests funded, but not defaults by those who fail to raise the fund. Our estimation on the default might be contaminated by the sample selection bias. We employ Heckman (1979) selection model to address this concern. In the first stage, we estimate the selection model of the probability of funding success (*SUCCESS*). In the second stage, the Probit model is used to treat *DEFAULT* as the dependent variable and other information as the independent variable for regression. A convincing implementation of Heckman selection model is to identify from the first stage choice model at least one exogenous independent variable that can be validly excluded from the vector of explanatory variables in the second stage regression (Little 1985; Lin & Su 2008; Bayar & Chemmanur 2012; Yuan *et al.* 2016; Boubakri *et al.* 2018; Cole & Sokolyk 2018; Daher & Ismail 2018; Dutordoir *et al.* 2018; Hasan *et al.* 2018; Jiang *et al.* 2018; Lockhart & Unlu 2018; Signori & Vismara 2018; Yuan & Wen 2018; Yang *et al.* 2019).

We leverage the peer effect for identification. The important role of peers in forming financial decisions has been well recognized in finance literature. For example, Leary and Roberts (2014) acknowledge that firms' financing decisions are in large part responses to the financing decisions of peer firms. We borrow from these studies and develop an instrument named *Me_SUCCESS* for the model identification. It is the average loan success rate of borrowers with similar interest rate, borrowing amount, and loan description length. We believe that loan success rate of peers with similar characteristics will affect funding probability of an individual borrower, but not this borrower's probability of default.

The estimation results are shown in Table 13. Column (1) reports the first step estimation on *SUCCESS*. The coefficient on *Me_SUCCESS* is positively significant, implying the higher the funding success rate of the peers, the higher the likelihood for a borrower to get loan application funded. Column (2) presents the endogeneity-adjusted estimate on default where Inverse Mill's Ratio (IMR) estimated by the first stage is added. The coefficient on *IMR* is negative, but not significant, indicating the influence of sample selection bias is not obvious. The coefficient on *DSCORE* is 0.177, which is significant and similar in size to the baseline estimation, meaning that our conclusions are robust after controlling for the sample selection bias.

********** Insert Table 13 here**********

5.2 Instrumental Variable Estimation

Our results may be affected by the omitted variables. For example, the borrowers who need fund urgently may choose to disclose as much information as possible. In this paper, we employ the instrumental variable (IV) regression to address these concerns. To mitigate the effect of omitted variables on our basic conclusion, first of all we need to find a suitable instrumental variable which should not directly correlate to funding success and interest rate but can exert a direct impact on voluntary disclosure by the borrowers. Considering that peer effect plays an important role in financial decisions (Leary & Roberts 2014), we utilize peer-borrower effect as a candidate. Leary and Roberts (2014) find that listed firms greatly affected by the peers in the same industry for financial decisions. A large number of corporate finance literatures also use the industrial average to construct the exogenous instrument variable (Chen 2015; Zhang *et al.* 2016; Kim *et al.* 2017; Adhikari & Agrawal 2018; Eom 2018; Hasan & Cheung 2018; Huang & Mazouz 2018; Jiang & Yuan 2018; Ward *et al.* 2018). Huang and Mazouz (2018) propose that firms in the same industry tend to adopt the similar corporate policy and use the natural logarithm of the industry average excess cash as the instrument variable of the firm's excess cash. Eom (2018) employs the industry average of the logarithm of oversubscription in the recent five IPOs as the instrument variable for oversubscription. Following those literatures, we believe that a borrower's decision on information disclosure is largely affected by the amount of information disclosed by his or her peers. To define the peers, we classify the borrowers into different categories according to their borrowing rate (low, median and high), the borrowing amount (low, median and high) and loan description length (low, median and high). The average amount of information disclosure by each category (Me_DSCORE) is then used as the instrument for the amount of information voluntarily disclosed by a borrower in this category.

Table 14 report the IV Probit and 2SLS regression results. The first stage regression result shown in Column (1) indicates that the information disclosure by the peers is a strong predictor of the information disclosed by an individual borrower. Moreover, the F-statistic shown at the bottom is 131.386. According to Staiger and Stock (1994), the suggested critical F-value is 18233 when the number of instruments is one. With the F-statistic much greater than 10, we can reject the null that the coefficient on the instrument is insignificantly different from zero at 1% level, excluding the concern of weak instrument. The second-stage regression results shown in Columns (2) to (3) are in line with the baseline estimations. The Wald test implies the necessity to address the endogeneity of DSCORE. Borrowers with more voluntary information disclosure have a significantly higher success rate of borrowing and higher interest rate.

**********Insert Table 14 here**********

6. Robustness Check

In this section, we do several robustness checks to further prove the validity of our findings reported in the previous session.

6.1 Probit and Possion Estimation

Regarding that Probit model is also suitable for binary variable estimation and has been widely used in economic research (Blundell & Powell 2004; Nyberg 2012), we re-estimate the impact of information disclosure on funding success and the probability of default with Probit model. At the same time, the interest rate limit set by Renrendai for borrowers is "no more than four times the benchmark interest rate of the central bank in the same period". Therefore, we also use Tobit model to re-estimate the impact of information disclosure on interest rate. In the Tobit model we set the upper bound on the interest rate to 24. As shown in Table 15, after controlling for other factors, borrowers' voluntary information disclosure is still positively and significantly related with funding success, interest rate, and the probability of default. Larger amount of disclosure is associated with higher probability of funding success, loan interest rate, and the probability of default.

**********Insert Table 15 here**********

6.2 Sample Adjustment

In this subsection, we adjust the sample to exclude the loan listings with extreme value of borrowing amount and borrowing rate. According to the regulation[4] recently issued by China Banking Regulatory Commission, a person cannot borrow over 200,000 RMB at the same P2P lending platform. Moreover, the highest annual borrowing rate of P2P lending cannot exceed four times of bank annual interest rate. According to our calculation, the maximum borrowing rate is 24% under the current regulation framework. Thus, in robustness tests, we exclude the loan listings that don't match the regulation requirements. Table 16 reports the estimation results for the loan listings whose borrowing amount is less than 200,000 RMB and borrowing rate is lower than 24%. We find that voluntary information disclosures are still positively and significantly associated with funding success, interest rate, and the probability of default.

**********Insert Table 16 here**********

6.3 The Quality of Voluntary Information Disclosure

From the logic of this paper, in fact, we have assumed that the quality of information provided by borrowers will have an impact on investors, and different information can reflect the quality of borrowers. Because, if all the information results are the same, from the perspective of investors, this is no different from the borrower did not disclose information, so there is no information disclosure signal. From the perspective of borrowers, if there is no difference in

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[4]On 24 August 2016, the Chinese government released the Interim Measures on Administration of the Business Activities of Peer-to-Peer Lending Information Intermediaries to crack down illegal fundraising activities through online finance so as to prevent financial risks and potential social unrest.

the impact of the quality of information disclosed to lenders, then the choice of disclosure and non-disclosure of such information will not have any impact on the loan outcome, so there will be no manipulation of information disclosure. In this regard, we examined the relationship between the borrower's education level, work experience, income level, company size and marital status, as well as funding success, interest rate, and the probability of default the borrower under the condition of full disclosure of information. The results are shown in table 17-19. It can be seen that different types of information quality do have significant differences between funding success, interest rate, and the probability of default. Therefore, it can be considered that the logical premise of this paper exists.

**********Insert Table 17 here**********
**********Insert Table 18 here**********
**********Insert Table 19 here**********

6.4 Additional Tests

To avoid estimation bias and ensure the solidness of our conclusion, we do some additional robustness checks. But we don't report the results due to space constraint. First, we exclude loan listings that are under repayment or defaulted from the sample, and redo empirical analysis. Second, we divide the samples into several subgroups according to whether the borrower owns housing property or car, whether borrowing rate, term, borrowers' age, the lengths of borrowing title and loan description are above or lower than the median value. Third, we re-estimate the models using the Bootstrap (100) standard error. All the results show that the conclusions above are robust.

6. Conclusions

The information asymmetry at the online P2P lending market motivates us to explore the role of voluntary disclosures as a bridging tool of the information gap between the borrowers and investors. We use data from Renrendai, one of the largest peer-to-peer lending platforms in China, to investigate the impact of voluntary information disclosure on the investment decisions. We find that the voluntary information disclosure is positively associated with funding probability, as well as the probability of default.

We find evidence of moral hazard behavior by borrowers. They voluntary disclose more information in order to manipulate investors. We are inclined to call such behavior a "*disclosure trap"*. Our results imply the possibility of information manipulation by the borrowers in Chinese P2P market. In other words, the results reveal a dark side of P2P lending confirming borrowers' Moral Hazard behavior. Poor-quality borrowers exploit the high level of information asymmetry and the lack of hard information by disclosing more information to capture funding however with a premediated intention to default. However, lenders are able to distinguish creditworthy borrowers with the help of information disclosed voluntarily even though hard facts like credit scores are not available. Despite the *disclosure trap*, lenders are smart enough to recognize the default risk associated with voluntary information disclosure under the condition of "*cheap talk*". It is still the best choice for lenders to invest in loan listings with more voluntary information disclosure, because these loan listings have higher expected profit and lower default losses.

Our results lead to several interesting discussions. On the one hand, borrowers who dare to disclose more information are more likely to be trusted by lenders than other borrowers. As the saying goes, "*in order not to let the lie be exposed, one lie after another can only be used to protect the first lie*". The more misinformation there is, the more loopholes there are, and the more likely it is to be found out, and lenders are smart. Based on the assumption that there is no way out, investors are more likely to favor borrowers who have the guts to disclose more. On the other hand, borrowers are more willing to use misleading information to attract investors.

Our study has strong implications for policy makers. Despite its substantial benefits, P2P lending also raises safety concerns. P2P lending shares all of the risks associated with traditional "brick and mortar" lending including lending fraud, identity theft, money laundering, consumer privacy and data protection violations. These risks are then married to and amplified by the anonymity and ubiquity of the Internet. Lax regulation has helped the industry to prosper, but as it approaches meaningful size and market impact, it would be wise for regulation to play a bigger role. Globally, the existing legal framework and regulations covering P2P lending is patchy at best. Our research confirms that the degree of information asymmetry will be strengthened in emerging developing countries where the credit system is not developed and the market environment is not perfect. For the financial authorities, it is necessary to perfect the unified social credit evaluation system. America has developed the Social credit system, personal credit information collection does not require the information solicited in advance from the consent of the subject, only be used when the information subject advice, every citizen of the United States Social Security Number (Social Security Number, SSN) work includes personal information, illegal record, place of residence, house property, financial position, credit card payment status, the education, and marital status. China's current social credit system is in the process of construction and has not yet formed a unified social credit evaluation system. Although government departments have a large amount of personal information, citizens' personal information has not been Shared uniformly. In the absence of social credit conditions, any voluntary information disclosure is lack of effectiveness, so the urgent task is to establish a set of credit evaluation system to adapt to social development, improve the consequences of personal false disclosure of information, to achieve the deterrent effect on the system.

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Figure 1: Volume of P2P lending in China, 2013-2017

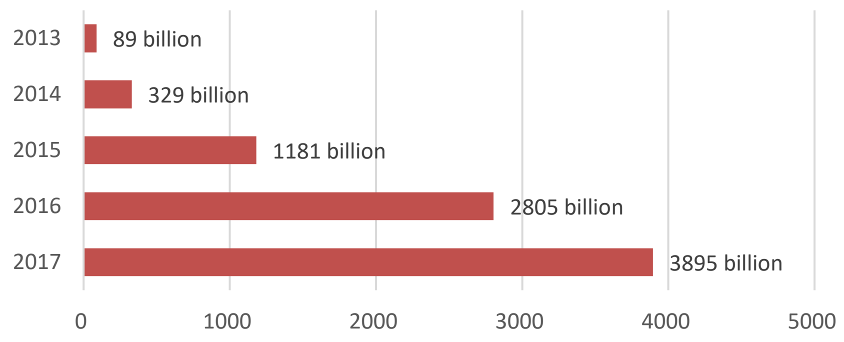

Figure 2: Example Loan Listing on Renrendai.com (Loan ID=469679)

Source: https://www.we.com/loan/469679

Table1: Variables and Definitions

Name	Definition
SUCCESS	1 if a loan listing is successfully funded, 0 otherwise
INTEREST	The interest rate offered by a borrower (%)
DEFAULT	1 if the funded loan has been default, and 0 otherwise
BIDS	The number of bids on a successful loan request
FundTime_M	The amount of time it takes to successfully raise funds (minutes)
Ver_Numb	The amount of information in a loan listing that has been verified by the platform
EP	Loan expected profit
LRR	Loan repayment ratio
DL	Default loss of a loan request
DSCORE	The amount of information Disclosure
DSCORE_ALL	1 if borrower disclose all information, 0 otherwise
DSCORE_NOR	The amount of information disclosure, except marital status and borrowing purpose
AMOUNT	Loan amount requested by the borrower (RMB)
MONTHS	Loan term requested by the borrower (months)
CREDIT	Credit grade of a borrower at the time the listing was created. values between 1(High Risk) and 7(AA)
POOR	1 if a borrower's Credit is high risk (HR), 0 otherwise
AGE	Age of the borrower in year
HOUSE	1 if a borrower owns a house, 0 otherwise
CAR	1 if a borrower owns a car, 0 otherwise
T_Length	The length of a loan title
D_Length	The length of a loan description (number of Chinese characters)
N_Length	The length of a of a borrower's nick name (number of Chinese characters)
Year	Year dummies for the periods of 2011-2015
Edu_Disclosure	1 if education level given, 0 otherwise
Worktime_Disclosure	1 if working experience given, 0 otherwise
Income_Disclosure	1 if income given, 0 otherwise
Marry_Disclosure	1 if marital status given, 0 otherwise
City_Disclosure	1 if residential city given, 0 otherwise
Firmsize_Disclosure	1 if company size given, 0 otherwise
Purpose_Disclosure	1 if purpose of loan given, 0 otherwise
Ind_Disclosure	1 if the working industry given, 0 otherwise
Position_Disclosure	1 if position given, 0 otherwise

Table 2: Summary Statistics of Information Disclosure

Panel A	Summary Statistics of Information Disclosure				
Variable	Mean		Sd		N
Edu_Disclosure	0.881		0.324		604,885
Worktime_Disclosure	0.700		0.458		604,885
Income_Disclosure	0.755		0.430		604,885
Marry_Disclosure	0.969		0.174		604,885
City_Disclosure	0.698		0.459		604,885
Firmsize_Disclosure	0.697		0.459		604,885
Purpose_Disclosure	0.998		0.044		604,885
Ind_Disclosure	0.697		0.459		604,885
Position_Disclosure	0.694		0.461		604,885
Panel B	**Difference Test**				
Variables	**SUCCESS==0**	**Mean1**	**SUCCESS==1**	**Mean2**	**MeanDiff**
DSCORE_ALL	577723	0.63	27111	0.9	-0.27***
DSCORE	577723	7.01	27111	8.75	-1.74***
DSCORE_NOR	577723	5.05	27111	6.75	-1.71***
Variables	**DEFAULT==0**	**Mean1**	**DEFAULT==1**	**Mean2**	**MeanDiff**
DSCORE_ALL	23018	0.89	4094	0.93	-0.04***
DSCORE	23018	8.74	4094	8.83	-0.10***
DSCORE_NOR	23018	6.74	4094	6.83	-0.10***
Variables	**DSCORE_ALL==0**	**Mean1**	**DSCORE_ALL==1**	**Mean2**	**MeanDiff**
SUCCESS	218823	0.01	386062	0.06	-0.05***
INTEREST	218823	12.76	386062	13.70	-0.93***
DEFAULT	2697	0.100	24415	0.160	-0.06***

Table 3: Correlation Matrix

	SUCCESS	INTEREST	DEFAULT	AMOUNT	MONTHS	CREDIT	AGE	
SUCCESS	1							
INTEREST	-0.0513*	1						
DEFAULT	0.3811*	-0.0089*	1					
AMOUNT	-0.0807*	0.0513*	-0.0301*	1				
MONTHS	-0.0856*	0.1395*	0.0158*	0.2182*	1			
CREDIT	0.4686*	-0.0400*	0	-0.0163*	-0.0777*	1		
AGE	0.0922*	0.0472*	0.0385*	0.2348*	0.0442*	0.0995*	1	
	SUCCESS	INTEREST	DEFAULT	HOUSE	CAR	T_Length	D_Length	N_Length
SUCCESS	1							
INTEREST	-0.0513*	1						
DEFAULT	0.3811*	-0.0089*	1					
HOUSE	0.1175*	0.0402*	0.0374*	1				
CAR	0.1268*	0.0039*	0.0266*	0.3634*	1			
T_Length	0.0730*	0.0521*	0.0176*	0.0647*	0.0607*	1		
D_Length	0.0727*	0.1215*	0.0193*	0.0991*	0.1024*	0.2416*	1	
N_Length	-0.1106*	-0.2143*	-0.0358*	-0.1337*	-0.0947*	-0.0232*	-0.1018*	1
	SUCCESS	INTEREST	DEFAULT	DSCORE_ALL	DSCORE	DSCORE_NOR		
SUCCESS	1							
INTEREST	-0.0513*	1						
DEFAULT	0.3811*	-0.0089*	1					
DSCORE_ALL	0.1182*	0.1575*	0.0509*	1				
DSCORE	0.1273*	0.1533*	0.0509*	0.8974*	1			
DSCORE_NOR	0.1277*	0.1524*	0.0511*	0.9021*	0.9982*	1		

Note:* p<0.05

Table 4: Summary Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
SUCCESS	604,885	0.0448	0.207	0	1
INTEREST	604,885	13.36	2.851	3	24.40
DEFAULT	27,112	0.151	0.358	0	1
DSCORE	604,885	7.090	2.827	0	9
DSCORE_NOR	604,885	5.123	2.764	0	7
DSCORE_ALL	604,885	0.638	0.481	0	1
FundTime_M	27112	122.8	574.4	0	6269
BIDS	27112	25.19	44.04	0	747
Ver_Numb	604,885	2.547	1.392	0	11
EP	604,885	19.82	11.43	-20.60	187.4
LRR	4,094	0.421	0.284	0	0.967
DL	604,885	-709.3	64239	-3108765	878353
AMOUNT	604,885	58956	90079	3000	500000
MONTHS	604,885	15.74	9.184	1	36
CREDIT	604,885	1.083	0.488	1	7
AGE	604,885	32.16	6.363	24	53
HOUSE	604,885	0.307	0.461	0	1
CAR	604,885	0.178	0.383	0	1
T_Length	604,885	13.72	7.128	1	108
D_Length	604,885	92.49	76.25	1	999
N_Length	604,885	9.706	3.184	1	32
YEAR=2011	604,885	0.0335	0.180	0	1
YEAR=2012	604,885	0.0468	0.211	0	1
YEAR=2013	604,885	0.0997	0.300	0	1
YEAR=2014	604,885	0.331	0.471	0	1
YEAR=2015	604,885	0.489	0.500	0	1

Table 5: Voluntary Disclosure and Funding Success

	(1) SUCCESS	(2) SUCCESS	(3) SUCCESS	(4) SUCCESS	(5) SUCCESS	(6) SUCCESS	(7) SUCCESS	(8) SUCCESS	(9) SUCCESS
Edu_Disclosure		5.239*** (14.81)							
Worktime_Disclosure			5.535*** (26.51)						
Income_Disclosure				6.342*** (16.81)					
City_Disclosure					3.223*** (49.87)				
Firmsize_Disclosure						0.985*** (37.27)			
Purpose_Disclosure							0.394* (1.78)		
Ind_Disclosure								0.985*** (37.25)	
Position_Disclosure									0.921*** (36.43)
lnAMOUNT	-0.607*** (-87.19)	-0.605*** (-85.92)	-0.607*** (-84.60)	-0.603*** (-84.51)	-0.613*** (-85.47)	-0.601*** (-84.87)	-0.607*** (-87.18)	-0.601*** (-84.88)	-0.603*** (-85.19)
INTEREST	-0.109*** (-38.26)	-0.109*** (-38.80)	-0.110*** (-39.89)	-0.109*** (-39.46)	-0.110*** (-39.83)	-0.110*** (-39.19)	-0.109*** (-38.27)	-0.110*** (-39.19)	-0.110*** (-39.22)
MONTHS	0.008*** (7.87)	0.007*** (6.42)	0.004*** (3.66)	0.005*** (5.17)	0.004*** (4.24)	0.005*** (4.91)	0.008*** (7.87)	0.005*** (4.91)	0.005*** (5.00)
CREDIT	1.476*** (95.10)	1.453*** (95.57)	1.404*** (96.46)	1.422*** (96.16)	1.432*** (99.24)	1.451*** (95.19)	1.476*** (95.10)	1.450*** (95.19)	1.453*** (95.15)
AGE	0.047*** (44.54)	0.048*** (45.94)	0.052*** (48.28)	0.050*** (47.17)	0.051*** (47.95)	0.047*** (44.80)	0.047*** (44.55)	0.047*** (44.79)	0.047*** (44.36)
HOUSE	0.469*** (27.27)	0.361*** (21.43)	0.146*** (8.91)	0.228*** (13.83)	0.161*** (9.70)	0.316*** (18.24)	0.469*** (27.27)	0.316*** (18.25)	0.330*** (19.05)
CAR	0.600*** (32.02)	0.551*** (30.19)	0.449*** (25.72)	0.488*** (27.56)	0.471*** (26.78)	0.540*** (29.31)	0.600*** (32.02)	0.540*** (29.31)	0.543*** (29.41)
T_Length	0.026*** (26.02)	0.023*** (23.50)	0.020*** (19.76)	0.021*** (21.00)	0.021*** (20.69)	0.024*** (24.02)	0.026*** (25.99)	0.024*** (24.02)	0.024*** (23.80)
D_Length	0.002*** (24.03)	0.002*** (22.69)	0.002*** (20.97)	0.002*** (21.24)	0.002*** (21.06)	0.002*** (22.10)	0.002*** (24.01)	0.002*** (22.10)	0.002*** (22.23)
N_Length	-0.152*** (-57.16)	-0.141*** (-53.68)	-0.110*** (-42.57)	-0.122*** (-47.14)	-0.114*** (-43.53)	-0.137*** (-51.33)	-0.152*** (-57.15)	-0.137*** (-51.33)	-0.139*** (-52.09)
_cons	1.288*** (17.50)	-3.876*** (-10.76)	-3.998*** (-18.40)	-4.903*** (-12.84)	-1.672*** (-17.06)	0.478*** (6.19)	0.894*** (3.84)	0.479*** (6.20)	0.588*** (7.68)
N	604885	604885	604885	604885	604885	604885	604885	604885	604885
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES
r2_p	0.301	0.313	0.337	0.328	0.332	0.309	0.301	0.309	0.308

Note: (1) This table reports Logit regression results. The Dependent variable is *SUCCESS* dummy, take value of 1 if a loan listing is fully funded, and 0 otherwise. *Edu_Disclosure* dummy, if borrower has disclosed education level. *Worktime_Disclosure* dummy , if borrower has disclosed work experience. *Income_Disclosure* dummy , if borrower has disclosed income. *City _Disclosure* dummy , if borrower has disclosed residential city. *Firmsize_Disclosure* dummy, if borrower has disclosed company size. *Purpose_Disclosure* dummy, if borrower has disclosed loan purpose. *Ind_Disclosure* dummy, if borrower has disclosed the work of the industry. *Position_Disclosure* dummy, 1 if borrower has disclosed the position. *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *INTEREST* is the interest rate that the borrower pays on the loan. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is number of observations. r2_p is pseudo R-square.

Table 6: Voluntary Disclosure Intensity and Funding Success

	(1) SUCCESS	(2) SUCCESS	(3) SUCCESS	(4) SUCCESS	(5) SUCCESS	(6) SUCCESS
DSCORE_ALL	1.110***	0.0343***				
	(43.80)	(42.33)				
DSCORE			0.344***	0.0106***		
			(65.80)	(61.03)		
DSCORE_NOR					0.346***	0.0107***
					(65.68)	(60.93)
lnAMOUNT	-0.606***	-0.0187***	-0.602***	-0.0186***	-0.602***	-0.0186***
	(-84.97)	(-78.93)	(-83.93)	(-78.21)	(-83.95)	(-78.22)
INTEREST	-0.111***	-0.00343***	-0.111***	-0.00343***	-0.111***	-0.00342***
	(-39.50)	(-39.01)	(-39.89)	(-39.39)	(-39.88)	(-39.38)
MONTHS	0.004***	0.000122***	0.003***	0.000102***	0.003***	0.000102***
	(3.77)	(3.768)	(3.15)	(3.150)	(3.16)	(3.156)
CREDIT	1.448***	0.0447***	1.428***	0.0441***	1.428***	0.0441***
	(95.85)	(103.8)	(95.85)	(104.2)	(95.84)	(104.2)
AGE	0.048***	0.00148***	0.049***	0.00152***	0.049***	0.00151***
	(44.91)	(43.82)	(45.90)	(44.75)	(45.87)	(44.72)
HOUSE	0.269***	0.00832***	0.204***	0.00630***	0.204***	0.00632***
	(15.52)	(15.45)	(12.12)	(12.09)	(12.14)	(12.12)
CAR	0.519***	0.0161***	0.487***	0.0150***	0.487***	0.0151***
	(28.39)	(28.09)	(27.14)	(26.89)	(27.15)	(26.90)
T_Length	0.023***	0.000710***	0.022***	0.000668***	0.022***	0.000670***
	(23.08)	(22.94)	(21.78)	(21.67)	(21.84)	(21.73)
D_Length	0.002***	5.23e-05***	0.002***	5.02e-05***	0.002***	5.03e-05***
	(21.89)	(21.81)	(21.03)	(20.96)	(21.05)	(20.98)
N_Length	-0.132***	-0.00408***	-0.123***	-0.00380***	-0.123***	-0.00381***
	(-49.15)	(-48.01)	(-46.67)	(-45.80)	(-46.69)	(-45.81)
_cons	0.483***		-1.507***		-0.836***	
	(6.29)		(-17.55)		(-10.28)	
Year	YES	YES	YES	YES	YES	YES
N	604885	604885	604885	604885	604885	604885
r2_p	0.312		0.321		0.321	

Note: (1) This table reports Logit regression results. The Dependent variable is *SUCCESS* dummy, take value of 1 if a loan listing is fully funded, and 0 otherwise. *DSCORE* is the borrower's disclosure score(see table 2). *DSCORE_ALL* dummy, if the borrower's disclosure score equal to 9. *DSCORE_NOR* is borrower's disclosure score (except marital status disclosure and purpose disclosure). *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *INTEREST* is the interest rate that the borrower pays on the loan. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *N_Length* is the length of a of a borrower's nick name. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is number of observations. r2_p is pseudo R-square. (3) Columns (2), (4) and (6) in show the corresponding marginal effects.

Table 7: Credit Score, Disclosure and Funding Probability

	(1) SUCCESS	(2) SUCCESS	(3) SUCCESS	(4) SUCCESS	(5) SUCCESS	(6) SUCCESS
DSCORE_ALL	-0.128**	-0.00372**				
	(-2.51)	(-2.506)				
DSCORE_ALL_POOR	1.454***	0.0422***				
	(24.23)	(24.05)				
DSCORE			-0.034**	-0.00100**		
			(-1.99)	(-1.989)		
DSCORE_POOR			0.422***	0.0123***		
			(22.73)	(22.55)		
DSCORE_NOR					-0.036**	-0.00106**
					(-2.10)	(-2.102)
DSCORE_NOR_POOR					0.426***	0.0124***
					(22.90)	(22.73)
POOR	-4.719***	-0.137***	-7.023***	-0.204***	-6.214***	-0.181***
	(-77.89)	(-75.41)	(-43.20)	(-42.50)	(-48.99)	(-48.06)
lnAMOUNT	-0.599***	-0.0174***	-0.596***	-0.0173***	-0.597***	-0.0173***
	(-82.42)	(-76.50)	(-81.73)	(-76.05)	(-81.74)	(-76.06)
INTEREST	-0.113***	-0.00329***	-0.113***	-0.00329***	-0.113***	-0.00329***
	(-41.15)	(-40.49)	(-41.45)	(-40.78)	(-41.44)	(-40.78)
MONTHS	0.004***	0.000115***	0.004***	0.000103***	0.004***	0.000103***
	(3.77)	(3.766)	(3.36)	(3.356)	(3.37)	(3.366)
CREDIT	0.080***	0.00231***	0.091***	0.00263***	0.091***	0.00263***
	(5.92)	(5.935)	(6.78)	(6.791)	(6.77)	(6.787)
AGE	0.048***	0.00140***	0.049***	0.00143***	0.049***	0.00143***
	(42.64)	(41.78)	(43.32)	(42.41)	(43.31)	(42.40)
HOUSE	0.243***	0.00706***	0.196***	0.00570***	0.196***	0.00571***
	(13.78)	(13.72)	(11.40)	(11.37)	(11.42)	(11.39)
CAR	0.478***	0.0139***	0.458***	0.0133***	0.458***	0.0133***
	(25.67)	(25.41)	(25.01)	(24.78)	(25.01)	(24.78)
T_Length	0.022***	0.000625***	0.021***	0.000599***	0.021***	0.000600***
	(21.25)	(21.12)	(20.45)	(20.34)	(20.47)	(20.37)
D_Length	0.002***	4.64e-05***	0.002***	4.49e-05***	0.002***	4.50e-05***
	(19.44)	(19.37)	(18.87)	(18.81)	(18.88)	(18.83)
N_Length	-0.118***	-0.00343***	-0.112***	-0.00325***	-0.112***	-0.00325***
	(-42.89)	(-41.93)	(-41.26)	(-40.47)	(-41.28)	(-40.48)
_cons	5.955***		6.069***		6.015***	
	(61.69)		(35.47)		(42.17)	
Year	YES	YES	YES	YES	YES	YES
N	604885	604885	604885	604885	604885	604885
r2_p	0.362		0.369		0.369	

Note: (1) This table reports Logit regression results. The Dependent variable is *SUCCESS* dummy, take value of 1 if a loan listing is fully funded, and 0 otherwise. *DSCORE* is the borrower's disclosure score(see table 2). *DSCORE_ALL* dummy, if the borrower's disclosure score equal to 9. *DSCORE_NOR* is borrower's disclosure score (except marital status disclosure and purpose disclosure). *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *INTEREST* is the interest rate that the borrower pays on the loan. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *N_Length* is the length of a of a borrower's nick name. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is number of observations. r2_p is pseudo R-square. (3) Columns (2), (4) and (6) in show the corresponding marginal effects.

Table 8: Voluntary Disclosure Intensity and Loan Default

	(1) DEFAULT	(2) DEFAULT	(3) DEFAULT	(4) DEFAULT	(5) DEFAULT	(6) DEFAULT	(7) DEFAULT
DSCORE_ALL		0.459***	0.0447***				
		(6.30)	(6.318)				
DSCORE				0.182***	0.0177***		
				(6.84)	(6.860)		
DSCORE_NOR						0.184***	0.0179***
						(6.90)	(6.922)
lnAMOUNT	0.301***	0.315***	0.0307***	0.319***	0.0311***	0.320***	0.0311***
	(10.64)	(11.06)	(11.12)	(11.19)	(11.25)	(11.20)	(11.26)
INTEREST	0.120***	0.119***	0.0116***	0.119***	0.0116***	0.119***	0.0116***
	(10.21)	(10.11)	(10.18)	(10.07)	(10.14)	(10.07)	(10.14)
MONTHS	0.060***	0.058***	0.00565***	0.058***	0.00562***	0.058***	0.00562***
	(24.57)	(23.43)	(24.79)	(23.28)	(24.63)	(23.28)	(24.63)
CREDIT	-2.093***	-2.098***	-0.204***	-2.100***	-0.204***	-2.099***	-0.204***
	(-27.54)	(-27.60)	(-30.86)	(-27.62)	(-30.88)	(-27.62)	(-30.88)
AGE	0.039***	0.038***	0.00370***	0.038***	0.00368***	0.038***	0.00368***
	(12.63)	(12.17)	(12.33)	(12.11)	(12.27)	(12.10)	(12.26)
HOUSE	-0.180***	-0.200***	-0.0195***	-0.204***	-0.0198***	-0.204***	-0.0198***
	(-4.34)	(-4.82)	(-4.833)	(-4.90)	(-4.911)	(-4.91)	(-4.915)
CAR	-0.139***	-0.128***	-0.0125***	-0.127***	-0.0123***	-0.127***	-0.0123***
	(-3.11)	(-2.87)	(-2.874)	(-2.83)	(-2.834)	(-2.83)	(-2.837)
T_Length	0.003	0.004	0.000344	0.004	0.000361	0.004	0.000363
	(0.93)	(1.30)	(1.304)	(1.37)	(1.371)	(1.38)	(1.378)
D_Length	0.001***	0.001***	5.94e-05***	0.001***	5.96e-05***	0.001***	5.95e-05***
	(3.02)	(2.82)	(2.819)	(2.83)	(2.830)	(2.83)	(2.827)
N_Length	0.009	0.009	0.000844	0.009	0.000832	0.009	0.000833
	(1.26)	(1.18)	(1.182)	(1.16)	(1.165)	(1.17)	(1.166)
_cons	-5.082***	-5.537***		-6.729***		-6.380***	
	(-15.24)	(-16.20)		(-16.34)		(-16.64)	
Year	YES	YES	YES	YES	YES	YES	YES
N	27112	27112		27112		27112	
r2_p	0.280	0.282		0.282		0.282	

Note: (1) This table reports Logit regression results. The Dependent variable is *DEFAULT* dummy, take value of 1 if the funded loan has been default, and 0 otherwise. *DSCORE* is the borrower's disclosure score(see table 2). *DSCORE_ALL* dummy, if the borrower's disclosure score equal to 9. *DSCORE_NOR* is borrower's disclosure score (except marital status disclosure and purpose disclosure). *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *INTEREST* is the interest rate that the borrower pays on the loan. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *N_Length* is the length of a of a borrower's nick name. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is number of observations. r2_p is pseudo R-square. (3) Columns (3), (5) and (7) in show the corresponding marginal effects.

Table 9: Verified Information and Loan Outcome

	(1) SUCCESS	(2) SUCCESS	(3) INTEREST	(4) INTEREST	(5) DEFAULT	(6) DEFAULT
DSCORE_ALL	1.888***		0.174***		0.162	
	(30.18)		(8.09)		(0.70)	
Ver_Numb	1.108***	2.010***	-0.007	-0.005	0.076	-0.279
	(51.25)	(32.34)	(-0.76)	(-0.18)	(1.61)	(-1.41)
Ver_Numb_DSCORE_ALL	-0.337***		-0.015		0.043	
	(-15.51)		(-1.62)		(0.89)	
DSCORE		0.642***		0.024***		-0.045
		(38.00)		(3.64)		(-0.47)
Ver_Numb_DSCORE		-0.139***		-0.002		0.044**
		(-19.97)		(-0.53)		(1.99)
lnAMOUNT	-0.732***	-0.735***	0.028***	0.028***	0.296***	0.298***
	(-79.82)	(-79.94)	(8.93)	(8.94)	(10.30)	(10.39)
INTEREST	-0.133***	-0.132***			0.115***	0.114***
	(-37.30)	(-37.64)			(9.74)	(9.70)
MONTHS	0.008***	0.008***	0.065***	0.066***	0.059***	0.058***
	(6.63)	(6.78)	(161.38)	(162.05)	(23.62)	(23.47)
CREDIT	0.588***	0.587***	-0.464***	-0.466***	-2.113***	-2.113***
	(32.12)	(32.58)	(-56.00)	(-56.22)	(-27.88)	(-27.87)
AGE	0.042***	0.043***	0.000	0.000	0.038***	0.038***
	(31.77)	(32.58)	(0.77)	(0.90)	(12.18)	(12.12)
HOUSE	-0.178***	-0.205***	-0.111***	-0.106***	-0.248***	-0.249***
	(-8.86)	(-10.43)	(-13.68)	(-13.07)	(-5.88)	(-5.90)
CAR	-0.060***	-0.069***	-0.221***	-0.219***	-0.196***	-0.193***
	(-2.63)	(-3.05)	(-24.84)	(-24.60)	(-4.28)	(-4.23)
T_Length	0.013***	0.012***	0.027***	0.026***	0.003	0.003
	(11.29)	(10.36)	(52.88)	(52.74)	(1.21)	(1.27)
D_Length	0.001***	0.001***	0.001***	0.001***	0.001**	0.001**
	(14.66)	(14.45)	(16.15)	(16.15)	(2.38)	(2.40)
N_Length	-0.095***	-0.088***	-0.050***	-0.051***	0.019***	0.020***
	(-30.45)	(-28.76)	(-50.34)	(-50.55)	(2.61)	(2.63)
_cons	-0.006	-3.869***	11.413***	11.348***	-5.607***	-5.057***
	(-0.06)	(-22.51)	(294.47)	(167.62)	(-13.86)	(-5.49)
Year	YES	YES	YES	YES	YES	YES
N	604885	604885	604885	604885	27112	27112
r2_p/a	0.460	0.466	0.305	0.305	0.285	0.285

Note: (1) This table reports Logit and OLS regression results. The dependent variables are (i) *SUCCESS* dummy, take value of 1 if a loan listing is fully funded, and 0 otherwise. (ii) *INTEREST*, the interest rate that the borrower pays on the loan. (iii) *DEFAULT*, taking value of 1 if the funded loan has been default, and 0 otherwise; *DSCORE* is the borrower's disclosure score(see table 2). *DSCORE_ALL* dummy, if the borrower's disclosure score equal to 9. *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *N_Length* is the length of a of a borrower's nick name. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and Z/T-statistics are reported in parentheses. N is number of observations. r2_a/p is adjusted R-square(pseudo R-square).

Table 10: Voluntary Disclosure Intensity and Risk Identification

	(1) DEFAULT	(2) DEFAULT	(3) FundTime_M	(4) BIDS
default_risk			721.161**	180.129***
			(2.02)	(7.81)
DSCORE	0.174***	0.182***		
	(6.84)	(6.84)		
lnAMOUNT		0.319***	-125.241	-28.884***
		(11.19)	(-1.11)	(-4.00)
INTEREST		0.119***	-94.612**	-21.753***
		(10.07)	(-2.20)	(-7.92)
MONTHS		0.058***	-40.808**	-10.732***
		(23.28)	(-1.97)	(-8.03)
CREDIT		-2.100***	1498.271**	378.442***
		(-27.62)	(2.00)	(7.82)
AGE		0.038***	-26.603**	-6.653***
		(12.11)	(-1.96)	(-7.59)
HOUSE		-0.204***	123.664*	34.505***
		(-4.90)	(1.72)	(7.38)
CAR		-0.127***	69.978	20.808***
		(-2.83)	(1.51)	(7.08)
T_Length		0.004	-3.379**	-0.760***
		(1.37)	(-2.50)	(-8.75)
D_Length		0.001***	-0.207	-0.088***
		(2.83)	(-0.91)	(-6.01)
N_Length		0.009	-1.824	-1.166***
		(1.16)	(-0.55)	(-5.51)
_cons	-3.259***	-6.729***	1527.449	355.500***
	(-14.46)	(-16.34)	(1.26)	(4.59)
Year	NO	YES	YES	YES
N	27112	27112	27112	27112
r2_p/a	0.002	0.282	0.153	0.476

Note: (1) This table reports Logit and OLS regression results. The dependent variables are (i) *DEFAULT*, taking value of 1 if the funded loan has been default, and 0 otherwise; (ii) *FundTime_M*, the amount of time it takes to successfully raise funds; (iii) *BIDS*, the number of lenders on the loan. *DSCORE* is the borrower's disclosure score(see table 2). *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *INTEREST* is the interest rate that the borrower pays on the loan. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *N_Length* is the length of a of a borrower's nick name. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and Z/T-statistics are reported in parentheses. N is number of observations. r2_a/p is adjusted R-square(pseudo R-square).

Table 11: Voluntary Disclosure Intensity and Interest Rate

	(1) INTEREST	(2) INTEREST	(3) INTEREST	(4) INTEREST
DSCORE_ALL		0.133***		
		(19.19)		
DSCORE			0.020***	
			(17.72)	
DSCORE_NOR				0.020***
				(17.12)
lnAMOUNT	0.025***	0.028***	0.028***	0.028***
	(8.17)	(9.07)	(9.08)	(9.05)
MONTHS	0.066***	0.065***	0.066***	0.066***
	(164.01)	(161.37)	(162.20)	(162.24)
CREDIT	-0.493***	-0.492***	-0.493***	-0.493***
	(-68.54)	(-68.61)	(-68.70)	(-68.70)
AGE	-0.000	0.000	0.000	0.000
	(-0.24)	(0.27)	(0.44)	(0.43)
HOUSE	-0.074***	-0.115***	-0.111***	-0.110***
	(-9.86)	(-14.30)	(-13.71)	(-13.61)
CAR	-0.207***	-0.229***	-0.227***	-0.226***
	(-23.73)	(-25.83)	(-25.58)	(-25.53)
T_Length	0.027***	0.026***	0.026***	0.026***
	(53.87)	(52.62)	(52.46)	(52.52)
D_Length	0.001***	0.001***	0.001***	0.001***
	(16.96)	(16.01)	(16.02)	(16.05)
N_Length	-0.053***	-0.050***	-0.050***	-0.050***
	(-55.94)	(-50.33)	(-50.44)	(-50.48)
_cons	11.537***	11.429***	11.369***	11.408***
	(348.91)	(340.63)	(329.53)	(335.66)
Year	YES	YES	YES	YES
N	604885	604885	604885	604885
r2_a	0.3047	0.3051	0.3050	0.3050

Note: (1) This table reports OLS regression results. The Dependent variable is *INTEREST*, the interest rate that the borrower pays on the loan. *DSCORE* is the borrower's disclosure score(see table 2). *DSCORE_ALL* dummy, if the borrower's disclosure score equal to 9. *DSCORE_NOR* is borrower's disclosure score (except marital status disclosure and purpose disclosure). *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *N_Length* is the length of a of a borrower's nick name. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and T-statistics are reported in parentheses. N is number of observations. r2_a is adjusted R-square.

Table 12: Voluntary Disclosure Intensity and Loan Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	EP	LRR	DL	EP	LRR	DL	EP	LRR	DL
DSCORE_ALL	0.013**	-0.021	-2.8e+03***						
	(1.96)	(-1.19)	(-17.54)						
DSCORE				0.003***	-0.009	-467.853***			
				(2.75)	(-1.46)	(-17.92)			
DSCORE_NOR							0.003***	-0.010	-482.712***
							(2.94)	(-1.46)	(-18.08)
lnAMOUNT	-2.424***	-0.008	-487.777***	-2.424***	-0.008	-497.684***	-2.424***	-0.008	-497.734***
	(-827.47)	(-1.18)	(-3.44)	(-827.19)	(-1.22)	(-3.51)	(-827.25)	(-1.22)	(-3.51)
INTEREST	0.782***	-0.007**	2270.494***	0.782***	-0.007**	2268.830***	0.782***	-0.007**	2268.664***
	(218.69)	(-2.55)	(67.48)	(218.75)	(-2.53)	(67.43)	(218.75)	(-2.54)	(67.43)
MONTHS	-0.493***	0.001	2054.188***	-0.493***	0.001	2051.611***	-0.493***	0.001	2051.664***
	(-1230.01)	(1.07)	(177.55)	(-1230.38)	(1.11)	(177.60)	(-1230.42)	(1.11)	(177.61)
CREDIT	12.729***	0.052***	-2.2e+04***	12.729***	0.052***	-2.2e+04***	12.729***	0.052***	-2.2e+04***
	(353.63)	(4.37)	(-31.42)	(353.55)	(4.39)	(-31.41)	(353.55)	(4.39)	(-31.40)
AGE	-0.320***	-0.001	1944.035***	-0.320***	-0.001	1941.069***	-0.320***	-0.001	1940.977***
	(-565.46)	(-1.58)	(115.91)	(-564.20)	(-1.57)	(115.74)	(-564.17)	(-1.57)	(115.74)
HOUSE	1.416***	-0.033***	-6.5e+03***	1.415***	-0.033***	-6.4e+03***	1.414***	-0.033***	-6.4e+03***
	(175.72)	(-3.55)	(-36.49)	(174.92)	(-3.51)	(-36.03)	(174.73)	(-3.52)	(-35.96)
CAR	1.117***	0.056***	-3.5e+03***	1.117***	0.056***	-3.5e+03***	1.117***	0.056***	-3.5e+03***
	(112.00)	(5.42)	(-14.19)	(111.84)	(5.42)	(-14.11)	(111.81)	(5.42)	(-14.09)
T_Length	-0.012***	0.000	126.619***	-0.012***	0.000	129.433***	-0.012***	0.000	129.349***
	(-21.42)	(0.26)	(11.31)	(-21.44)	(0.24)	(11.53)	(-21.45)	(0.24)	(11.52)
D_Length	-0.005***	0.000	48.472***	-0.005***	0.000	48.601***	-0.005***	0.000	48.602***
	(-91.18)	(0.77)	(28.92)	(-91.15)	(0.79)	(28.97)	(-91.16)	(0.79)	(28.97)
N_Length	-0.033***	0.002	39.578	-0.033***	0.002	34.305	-0.033***	0.002	33.415
	(-34.74)	(1.12)	(1.51)	(-34.77)	(1.12)	(1.31)	(-34.71)	(1.12)	(1.28)
_cons	36.104***	0.529***	-9.2e+04***	36.091***	0.594***	-9.0e+04***	36.095***	0.575***	-9.1e+04***
	(517.82)	(7.06)	(-46.78)	(520.86)	(6.31)	(-45.73)	(519.38)	(6.65)	(-46.25)
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	604885	4094	604885	604885	4094	604885	604885	4094	604885
r2_a	0.956	0.022	0.189	0.956	0.023	0.189	0.956	0.023	0.189

Note: (1) This table reports OLS regression results. The dependent variables are (i) *EP*, expected profit of a loan listing; (ii) *LRR*, repayment ratio of a loan listing; (iii) *DL*, default loss of a loan listing; *DSCORE* is the borrower's disclosure score(see table 2). *DSCORE_ALL* dummy, if the borrower's disclosure score equal to 9. *DSCORE_NOR* is borrower's disclosure score (except marital status disclosure and purpose disclosure). *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *INTEREST* is the interest rate that the borrower pays on the loan. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *N_Length* is the length of a of a borrower's nick name. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and T-statistics are reported in parentheses. N is number of observations. r2_a is adjusted R-square.

Table 13: Endogenous Concern (Heckman Two-Step)

	(1) SUCCESS	(2) DEFAULT
Me_SUCCESS	5.009***	
	(60.92)	
DSCORE	0.147***	0.177***
	(68.44)	(6.21)
IMR		-0.034
		(-0.42)
lnAMOUNT	-0.193***	0.329***
	(-53.87)	(8.99)
INTEREST	-0.030***	0.121***
	(-22.71)	(9.23)
MONTHS	0.002***	0.058***
	(3.41)	(22.75)
CREDIT	0.690***	-2.118***
	(90.94)	(-22.51)
AGE	0.024***	0.037***
	(46.41)	(10.45)
HOUSE	0.104***	-0.206***
	(12.99)	(-4.90)
CAR	0.245***	-0.134***
	(28.05)	(-2.80)
T_Length	0.009***	0.003
	(17.69)	(1.21)
D_Length	0.000*	0.001***
	(1.86)	(2.64)
N_Length	-0.059***	0.010
	(-46.71)	(1.23)
_cons	-2.255***	-6.705***
	(-50.06)	(-16.03)
Year	YES	YES
N	604885	27112
r2_p	0.350	0.282

Note: (1) This table reports Heckman two-step regression result on the Probability of Default. In column (1), the Dependent variable is SUCCESS, taking value of 1 if a loan listing is fully funded, and 0 otherwise. In column (2), the Dependent variable is DEFAULT dummy, taking value of 1 if the funded loan has been default, and 0 otherwise. *DSCORE* is the borrower's disclosure score(see table 2). *IMR* is the inverse Mills ratio. *Me_SUCCESS* is the average funding success rate of a borrower's peers. *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *INTEREST* is the interest rate that the borrower pays on the loan. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *N_Length* is the length of a of a borrower's nick name. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is number of observations. r2_p is pseudo R-square.

Table 14: Endogenous Concern (2SLS and IVProbit)

	(1) DSCORE	(2) INTEREST	(3) SUCCESS
Me_DSCORE	0.396***		
	(66.78)		
DSCORE		3.668***	0.253***
		(63.30)	(18.04)
lnAMOUNT	-0.131***	0.554***	-0.265***
	(-42.88)	(39.39)	(-43.08)
INTEREST	-0.007***		-0.054***
	(-5.92)		(-42.21)
MONTHS	0.019***	-0.027***	-0.002***
	(46.79)	(-13.06)	(-2.72)
CREDIT	0.022***	-0.535***	0.682***
	(5.02)	(-21.45)	(65.17)
AGE	-0.018***	0.066***	0.025***
	(-35.63)	(29.21)	(51.01)
HOUSE	1.827***	-6.832***	-0.102***
	(329.75)	(-61.85)	(-3.37)
CAR	0.991***	-3.865***	0.129***
	(163.01)	(-57.70)	(6.56)
T_Length	0.027***	-0.087***	0.007***
	(63.43)	(-34.98)	(9.25)
D_Length	0.001***	-0.007***	0.001***
	(14.60)	(-35.09)	(10.49)
N_Length	-0.163***	0.555***	-0.038***
	(-155.87)	(53.37)	(-11.17)
_cons	6.141***	-19.999***	-1.732***
	(123.76)	(-38.95)	(-13.88)
N	604885	604885	604885
F statistics	18233		
Wald test			0.00
r2_a	0.269		

Note: (1) This table reports 2SLS and IVProbit regression results. (2) The Dependent variable in column (1) is *DSCORE*, is the borrower's disclosure score(see table 2). The Dependent variable in column (2) is *INTEREST*, is the interest rate that the borrower pays on the loan. The Dependent variable in column (3) is *SUCCESS* dummy, take value of 1 if a loan listing is fully funded, and 0 otherwise. *Me_DSCORE* is the average amount of information disclosed by the peers. *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *INTEREST* is the interest rate that the borrower pays on the loan. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *Year* is Year dummy. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *N_Length* is the length of a of a borrower's nick name. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and T/Z-statistics are reported in parentheses. N is number of observations. r2_a is adjusted R-square.

Table 15: Robust Check 1: Probit and Tobit Model

	(1) SUCCESS	(2) INTEREST	(3) DEFAULT	(4) SUCCESS	(5) INTEREST	(6) DEFAULT	(7) SUCCESS	(8) INTEREST	(9) DEFAULT
DSCORE_ALL	0.492***	0.135***	0.249***						
	(46.52)	(19.15)	(6.06)						
DSCORE				0.149***	0.020***	0.100***			
				(71.08)	(17.68)	(6.78)			
DSCORE_NOR							0.150***	0.020***	0.101***
							(71.03)	(17.08)	(6.84)
lnAMOUNT	-0.289***	0.027***	0.181***	-0.291***	0.027***	0.183***	-0.291***	0.027***	0.183***
	(-86.33)	(8.55)	(11.21)	(-85.29)	(8.57)	(11.34)	(-85.30)	(8.54)	(11.35)
INTEREST	-0.053***		0.063***	-0.053***		0.063***	-0.053***		0.063***
	(-40.20)		(9.37)	(-40.68)		(9.33)	(-40.67)		(9.33)
MONTHS	0.001***	0.065***	0.034***	0.001*	0.065***	0.034***	0.001*	0.065***	0.034***
	(2.63)	(158.49)	(23.31)	(1.95)	(159.31)	(23.11)	(1.95)	(159.35)	(23.10)
CREDIT	0.717***	-0.498***	-0.946***	0.710***	-0.498***	-0.948***	0.710***	-0.498***	-0.948***
	(93.21)	(-68.91)	(-22.06)	(93.05)	(-69.01)	(-22.10)	(93.05)	(-69.00)	(-22.10)
AGE	0.023***	0.000	0.022***	0.024***	0.000	0.021***	0.024***	0.000	0.021***
	(46.50)	(0.22)	(12.13)	(47.55)	(0.39)	(12.07)	(47.52)	(0.38)	(12.06)
HOUSE	0.133***	-0.116***	-0.111***	0.101***	-0.112***	-0.113***	0.102***	-0.111***	-0.113***
	(16.59)	(-14.21)	(-4.68)	(12.89)	(-13.62)	(-4.78)	(12.91)	(-13.52)	(-4.78)
CAR	0.262***	-0.231***	-0.064**	0.246***	-0.229***	-0.063**	0.246***	-0.229***	-0.063**
	(30.29)	(-25.69)	(-2.52)	(28.84)	(-25.44)	(-2.48)	(28.84)	(-25.39)	(-2.48)
T_Length	0.011***	0.027***	0.002	0.011***	0.027***	0.002	0.011***	0.027***	0.002
	(23.74)	(52.22)	(1.48)	(22.23)	(52.06)	(1.55)	(22.29)	(52.11)	(1.55)
D_Length	0.001***	0.001***	0.000***	0.001***	0.001***	0.000***	0.001***	0.001***	0.000***
	(21.05)	(15.95)	(2.61)	(20.17)	(15.95)	(2.60)	(20.19)	(15.98)	(2.60)
N_Length	-0.061***	-0.050***	0.004	-0.058***	-0.050***	0.004	-0.058***	-0.050***	0.004
	(-49.62)	(-49.78)	(0.95)	(-46.78)	(-49.89)	(0.94)	(-46.80)	(-49.93)	(0.95)
_cons	-0.032	11.446***	-3.431***	-0.859***	11.385***	-4.094***	-0.568***	11.425***	-3.901***
	(-0.89)	(334.91)	(-18.06)	(-22.13)	(324.00)	(-17.82)	(-15.17)	(330.01)	(-18.25)
sigma									
_cons		2.417***			2.417***			2.417***	
		(527.69)			(527.66)			(527.66)	
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	604885	604885	27112	604885	604885	27112	604885	604885	27112
r2_p	0.318	0.072	0.272	0.326	0.072	0.272	0.326	0.072	0.272

Note: (1) This table reports Probit and Tobit regression results. The dependent variables are (i) *SUCCESS* dummy, take value of 1 if a loan listing is fully funded, and 0 otherwise. (ii) *INTEREST*, the interest rate that the borrower pays on the loan. (iii) *DEFAULT*, taking value of 1 if the funded loan has been default, and 0 otherwise; *DSCORE* is the borrower's disclosure score(see table 2). *DSCORE_ALL* dummy, if the borrower's disclosure score equal to 9. *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *N_Length* is the length of a of a borrower's nick name. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and Z/T-statistics are reported in parentheses. N is number of observations. r2_a/p is adjusted R-square(pseudo R-square).

Table 16: Robust Check 2: Loan listings with borrowing amount less than 200,000 yuan and Loan listings with borrowing rate lower than 24%

	(1) SUCCESS	(2) INTEREST	(3) DEFAULT	(4) SUCCESS	(5) INTEREST	(6) DEFAULT	(7) SUCCESS	(8) INTEREST	(9) DEFAULT
DSCORE_ALL	1.107***	0.133***	0.457***						
	(43.60)	(18.98)	(6.26)						
DSCORE				0.343***	0.020***	0.180***			
				(65.53)	(17.40)	(6.79)			
DSCORE_NOR							0.345***	0.019***	0.182***
							(65.41)	(16.81)	(6.85)
lnAMOUNT	-0.557***	0.036***	0.291***	-0.554***	0.036***	0.295***	-0.554***	0.036***	0.296***
	(-73.45)	(10.30)	(9.87)	(-72.60)	(10.32)	(10.00)	(-72.62)	(10.30)	(10.01)
INTEREST	-0.112***		0.121***	-0.112***		0.120***	-0.112***		0.120***
	(-38.90)		(10.10)	(-39.25)		(10.06)	(-39.24)		(10.06)
MONTHS	0.002*	0.066***	0.058***	0.001	0.066***	0.058***	0.001	0.066***	0.058***
	(1.87)	(155.63)	(23.33)	(1.31)	(156.44)	(23.19)	(1.31)	(156.48)	(23.19)
CREDIT	1.466***	-0.490***	-2.118***	1.444***	-0.491***	-2.120***	1.445***	-0.491***	-2.120***
	(93.14)	(-66.50)	(-27.50)	(93.12)	(-66.60)	(-27.51)	(93.11)	(-66.59)	(-27.51)
AGE	0.048***	-0.000	0.038***	0.049***	-0.000	0.038***	0.049***	-0.000	0.038***
	(44.81)	(-0.28)	(12.09)	(45.78)	(-0.12)	(12.03)	(45.75)	(-0.14)	(12.02)
HOUSE	0.274***	-0.114***	-0.204***	0.209***	-0.109***	-0.207***	0.209***	-0.109***	-0.207***
	(15.79)	(-13.93)	(-4.88)	(12.39)	(-13.32)	(-4.96)	(12.42)	(-13.22)	(-4.96)
CAR	0.522***	-0.218***	-0.124***	0.490***	-0.217***	-0.122***	0.490***	-0.216***	-0.122***
	(28.56)	(-23.96)	(-2.77)	(27.32)	(-23.72)	(-2.73)	(27.32)	(-23.67)	(-2.73)
T_Length	0.023***	0.027***	0.004	0.022***	0.027***	0.004	0.022***	0.027***	0.004
	(22.98)	(52.40)	(1.55)	(21.68)	(52.26)	(1.61)	(21.73)	(52.31)	(1.62)
D_Length	0.002***	0.001***	0.001**	0.002***	0.001***	0.001**	0.002***	0.001***	0.001**
	(21.83)	(15.80)	(2.40)	(20.98)	(15.81)	(2.41)	(21.00)	(15.84)	(2.41)
N_Length	-0.132***	-0.048***	0.008	-0.124***	-0.048***	0.008	-0.124***	-0.048***	0.008
	(-49.13)	(-47.57)	(1.09)	(-46.66)	(-47.70)	(1.07)	(-46.68)	(-47.74)	(1.07)
_cons	0.037	11.322***	-5.286***	-1.942***	11.263***	-6.471***	-1.271***	11.302***	-6.125***
	(0.46)	(308.57)	(-15.23)	(-21.83)	(300.22)	(-15.52)	(-15.01)	(304.96)	(-15.76)
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	576423	576423	26822	576423	576423	26822	576423	576423	26822
r2_p/a	0.308	0.304	0.280	0.317	0.304	0.281	0.316	0.304	0.281

Note: (1) This table reports Logit and OLS regression results. The dependent variables are (i) *SUCCESS* dummy, take value of 1 if a loan listing is fully funded, and 0 otherwise. (ii) *INTEREST*, the interest rate that the borrower pays on the loan. (iii) *DEFAULT*, taking value of 1 if the funded loan has been default, and 0 otherwise; *DSCORE* is the borrower's disclosure score(see table 2). *DSCORE_ALL* dummy, if the borrower's disclosure score equal to 9. *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *N_Length* is the length of a of a borrower's nick name. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and Z/T-statistics are reported in parentheses. N is number of observations. r2_a/p is adjusted R-square(pseudo R-square).

Table 17: Robust Check 3: Information Quality and Funding Success

	(1) SUCCESS	(2) SUCCESS	(3) SUCCESS	(4) SUCCESS	(5) SUCCESS
EDUCATION	0.329***				
	(34.11)				
WORKTIME		0.320***			
		(38.27)			
INCOME			0.321***		
			(41.75)		
Firmsize				0.229***	
				(31.81)	
Marry_Married					0.205***
					(11.53)
lnAMOUNT	-0.648***	-0.646***	-0.776***	-0.618***	-0.641***
	(-83.79)	(-83.73)	(-94.90)	(-79.44)	(-82.96)
INTEREST	-0.103***	-0.107***	-0.108***	-0.106***	-0.107***
	(-35.95)	(-37.40)	(-37.46)	(-37.05)	(-37.38)
MONTHS	0.007***	0.006***	0.017***	0.004***	0.007***
	(6.74)	(5.88)	(14.95)	(3.96)	(6.79)
CREDIT	1.372***	1.376***	1.376***	1.397***	1.409***
	(91.55)	(91.81)	(90.95)	(93.69)	(93.84)
AGE	0.055***	0.037***	0.047***	0.055***	0.049***
	(48.12)	(30.26)	(40.84)	(48.63)	(41.19)
HOUSE	0.118***	0.080***	0.177***	0.150***	0.133***
	(6.77)	(4.59)	(10.27)	(8.66)	(7.63)
CAR	0.407***	0.373***	0.237***	0.471***	0.380***
	(22.15)	(20.21)	(12.42)	(25.45)	(20.55)
T_Length	0.015***	0.017***	0.016***	0.017***	0.017***
	(14.22)	(15.73)	(15.23)	(16.28)	(15.92)
D_Length	0.002***	0.002***	0.002***	0.002***	0.002***
	(20.57)	(21.54)	(18.49)	(21.57)	(20.88)
N_Length	-0.108***	-0.108***	-0.109***	-0.108***	-0.109***
	(-38.98)	(-39.04)	(-39.38)	(-39.21)	(-39.91)
_cons	1.107***	1.594***	1.967***	0.872***	1.785***
	(13.58)	(19.82)	(24.81)	(10.52)	(22.19)
Year	YES	YES	YES	YES	YES
N	386062	386062	386062	386062	386062
r2_p	0.282	0.284	0.286	0.281	0.277

Note: (1) This table reports Logit regression results. The Dependent variable is *SUCCESS* dummy, take value of 1 if a loan listing is fully funded, and 0 otherwise. *DSCORE* is the borrower's disclosure score(see table 2). *DSCORE_ALL* dummy, if the borrower's disclosure score equal to 9. *DSCORE_NOR* is borrower's disclosure score (except marital status disclosure and purpose disclosure). *EDUCATION* is education achievement of a borrower. *WORKTIME* is borrowers' working experience. *INCOME* is monthly income of a borrower. *Firmsize* is the size of the company where the borrower works. *Marry_Married* dummy, take value of 1 if a borrower is married, and 0 otherwise. *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *INTEREST* is the interest rate that the borrower pays on the loan. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *N_Length* is the length of a of a borrower's nick name. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is number of observations. r2_p is pseudo R-square.

Table 18: Robust Check 3: Information Quality and Interest Rate

	(1) INTEREST	(2) INTEREST	(3) INTEREST	(4) INTEREST	(5) INTEREST
EDUCATION	-0.136***				
	(-25.59)				
WORKTIME		0.005			
		(1.01)			
INCOME			0.066***		
			(14.82)		
Firmsize				-0.036***	
				(-8.66)	
Marry_Married					-0.058***
					(-6.27)
lnAMOUNT	0.028***	0.020***	-0.007	0.017***	0.022***
	(6.45)	(4.65)	(-1.46)	(3.84)	(4.94)
MONTHS	0.052***	0.052***	0.054***	0.053***	0.052***
	(93.89)	(94.14)	(95.34)	(94.52)	(94.22)
CREDIT	-0.493***	-0.515***	-0.524***	-0.510***	-0.512***
	(-65.25)	(-68.10)	(-69.13)	(-67.66)	(-68.06)
AGE	0.002**	0.002**	0.001	0.002***	0.003***
	(2.41)	(2.49)	(1.06)	(2.74)	(4.75)
HOUSE	-0.101***	-0.120***	-0.119***	-0.117***	-0.109***
	(-11.28)	(-13.33)	(-13.35)	(-13.08)	(-11.98)
CAR	-0.231***	-0.234***	-0.265***	-0.242***	-0.225***
	(-23.88)	(-24.13)	(-26.97)	(-24.85)	(-22.94)
T_Length	0.030***	0.030***	0.029***	0.030***	0.030***
	(46.05)	(44.91)	(44.50)	(44.87)	(44.86)
D_Length	0.001***	0.001***	0.001***	0.001***	0.001***
	(11.51)	(11.24)	(10.61)	(11.09)	(11.17)
N_Length	-0.033***	-0.033***	-0.032***	-0.033***	-0.032***
	(-25.92)	(-25.32)	(-25.20)	(-25.54)	(-25.24)
_cons	11.752***	11.593***	11.658***	11.715***	11.558***
	(254.39)	(252.99)	(252.24)	(243.83)	(250.92)
Year	YES	YES	YES	YES	YES
N	386062	386062	386062	386062	386062
r2_a	0.279	0.278	0.278	0.278	0.278

Note: (1) This table reports OLS regression results. The Dependent variable is *INTEREST*, the interest rate that the borrower pays on the loan. *DSCORE* is the borrower's disclosure score(see table 2). *DSCORE_ALL* dummy, if the borrower's disclosure score equal to 9. *DSCORE_NOR* is borrower's disclosure score (except marital status disclosure and purpose disclosure). *EDUCATION* is education achievement of a borrower. *WORKTIME* is borrowers' working experience. *INCOME* is monthly income of a borrower. *Firmsize* is the size of the company where the borrower works. *Marry_Married* dummy, take value of 1 if a borrower is married, and 0 otherwise. *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *N_Length* is the length of a of a borrower's nick name. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and T-statistics are reported in parentheses. N is number of observations. r2_a is adjusted R-square.

Table 19: Robust Check 3: Information Quality and Loan Default

	(1) DEFAULT	(2) DEFAULT	(3) DEFAULT	(4) DEFAULT	(5) DEFAULT
EDUCATION	-0.559***				
	(-20.70)				
WORKTIME		-0.069***			
		(-3.10)			
INCOME			0.245***		
			(11.96)		
Firmsize				-0.210***	
				(-10.12)	
Marry_Married					0.076
					(1.61)
lnAMOUNT	0.336***	0.315***	0.108***	0.285***	0.313***
	(10.87)	(10.50)	(3.14)	(9.44)	(10.45)
INTEREST	0.117***	0.120***	0.119***	0.118***	0.120***
	(9.16)	(9.84)	(9.80)	(9.56)	(9.86)
MONTHS	0.060***	0.057***	0.063***	0.060***	0.057***
	(22.65)	(22.42)	(24.01)	(23.21)	(22.38)
CREDIT	-2.069***	-2.101***	-2.104***	-2.103***	-2.101***
	(-26.75)	(-27.23)	(-27.26)	(-27.17)	(-27.30)
AGE	0.035***	0.042***	0.035***	0.036***	0.037***
	(10.71)	(12.21)	(10.77)	(11.21)	(10.89)
HOUSE	-0.083*	-0.169***	-0.173***	-0.169***	-0.202***
	(-1.87)	(-3.87)	(-3.99)	(-3.90)	(-4.57)
CAR	-0.163***	-0.138***	-0.264***	-0.196***	-0.152***
	(-3.42)	(-2.94)	(-5.48)	(-4.16)	(-3.21)
T_Length	0.008***	0.003	0.003	0.003	0.003
	(2.67)	(1.18)	(0.89)	(1.08)	(1.22)
D_Length	0.001***	0.001***	0.001***	0.001***	0.001***
	(3.10)	(3.26)	(2.82)	(3.00)	(3.38)
N_Length	0.010	0.007	0.008	0.009	0.006
	(1.27)	(0.86)	(1.00)	(1.19)	(0.83)
_cons	-4.180***	-5.023***	-3.993***	-4.170***	-5.036***
	(-11.60)	(-14.43)	(-11.27)	(-11.67)	(-14.47)
Year	YES	YES	YES	YES	YES
N	24415	24415	24415	24415	24415
r2_p	0.305	0.285	0.291	0.289	0.284

Note: (1) This table reports Logit regression results. The Dependent variable is *DEFAULT* dummy, take value of 1 if the funded loan has been default, and 0 otherwise. *DSCORE* is the borrower's disclosure score(see table 2). *DSCORE_ALL* dummy, if the borrower's disclosure score equal to 9. *DSCORE_NOR* is borrower's disclosure score (except marital status disclosure and purpose disclosure). *EDUCATION* is education achievement of a borrower. *WORKTIME* is borrowers' working experience. *INCOME* is monthly income of a borrower. *Firmsize* is the size of the company where the borrower works. *Marry_Married* dummy, take value of 1 if a borrower is married, and 0 otherwise. *lnAmount* is natural log of loan amount(in RMB) requested by the borrower. *INTEREST* is the interest rate that the borrower pays on the loan. *MONTHS* is loan term(in months) requested by the borrower. *CREDIT* is credit grade of the borrower at the time the listing was created. *AGE* is age of borrower in year. *HOUSE* dummy, if borrower is a homeowner. *CAR* dummy, if borrower is a carowner. *T_Length* is the number of characters of a loan title. *D_Length* is the number of characters of a loan description. *N_Length* is the length of a of a borrower's nick name. *Year* is Year dummy. (2)*,**,*** indicate significance at 10%, 5%, 1% levels respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is number of observations. r2_p is pseudo R-square.